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Primary Wood-Using Mills and Forest Resources: Interactions between Wood Demand and Procurement Areas

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To the Graduate Council:

I am submitting herewith a dissertation written by Consuelo Brandeis entitled "Primary Wood-Using Mills and Forest Resources: Interactions between Wood Demand and Procurement Areas." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Natural Resources.

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Primary Wood-Using Mills and Forest Resources: Interactions between Wood Demand and Procurement Areas

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ABSTRACT

It is a common belief that the presence of forest industry and associated wood demand will result in forest management of procurement areas. The following essays examined the relationship between mill demand and procurement areas by assessing the likelihood of forest management and the ability to predict future wood output. The first study investigates the likelihood of forest management given proximity to mills using a multivariate probit model, incorporating forest characteristics and primary wood-using mill information collected by the USDA Forest Service Forest Inventory and Analysis and the Timber Products Output (TPO) survey. The second essay explores the use of vector autoregressive methods to forecast county pulpwood output using pulpwood production data collected by TPO. We evaluated a group of forecasting methods in the vector autoregressive family and compared the models forecast accuracy to that of the commonly used step-forward methodology. Results from the first study indicate that mill proximity has a low impact on private forest landowner management decisions. This information may prove useful to industry and state foresters when dealing with increases in demand arising from new markets, such as bioenergy. Forecasts from the second essay highlight the cross-county differences in terms of pulpwood output in response to national demand. While the macroeconomic series helped predict output activity in some counties, a group of counties displayed no correlation between product output and demand measured by the national variables. The results emphasize the need for disaggregated analysis to capture the dynamics of the procurement areas and primary mills.

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I Introduction

Although definitions of what constitutes a forest often center on classification of the trees by size and structure, a forest amounts to more than just the dominant vegetation. A forest is an ecosystem, home to a variety of living organisms. These ecosystems provide a variety of products and services, helping satisfy man's spiritual and physical needs alike. Forests also contribute to the health of the environment by performing a variety of functions. For instance, forest vegetation provides soil protection, helping control soil erosion. Likewise, forests help regulate the carbon cycle and provide habitat to support biodiversity.

The demands on forest ecosystems are varied and numerous. The question remains if forests can be sustainable given the demand from often conflicting interests such as timber and recreation. The renewable quality of forests brings the possibility for management to achieve both timber and non-timber benefits in a sustainable manner, i.e., forests managed in a way that satisfies existing needs for these goods and services, while securing the continued long-term availability of the resource. Rational forest owners will maximize utility, and though standing forests provide benefit, the level of utility proves subjective to landowner's preferences.

Recognition of the full range of goods and services provided by the forest ecosystems in the U.S. exists concurrently with a changing forestland ownership base. On one hand, forest industry continues divesting timberland holdings to investment organizations such as timber investment management organizations (TIMOs) and real estate investment trusts (REITs), whose objective include profit maximizing rather than mill procurement. Most TIMOs and REITs will manage to maximize financial returns. On the other hand, higher-income urban populations continue expanding into the suburban fringe in search of natural settings, resulting in dispersed, low density development and fragmented forestlands (Smith, Miles, Charles, & Pugh, 2009). These exurban forestland owners also bring a new set of objectives, where forestlands are held for non-timber utility including aesthetic, privacy, and recreational uses (Butler, 2008).

Data from 2007 by the USDA Forest Service (Smith et al., 2009) indicate that approximately 31 percent of U.S. timberland was publicly owned, with 19 percent being federal ownership. Corporate ownership accounted for about 21 percent and the remaining 49 percent was owned by private non-corporate owners. This last category includes family-owned forests and conservation groups. While the government manages federal lands for multiple uses, the ownership provides only marginal wood volumes when compared to volumes supplied from private lands. According to USDA Forest Service estimates, during 2006 private lands produced 91 percent of the total timber output, while federal lands contributed only three percent. Furthermore, the volume of timber harvested on federal lands declined by 57 percent between 1996 and 2006 (Smith et al., 2009). This trend resulted from a variety of factors influencing the Forest Service's management decisions, steering management to focus on non-timber benefits. As a consequence, forest industry relies more heavily on privately owned timberland to provide forest resources.

1. Problem Statement

The U.S. Census (2011) estimates that U.S. population increased by 13 percent from 1990 to 2000 and per-capita income rose by 16 percent between 1990 and 2009. Population growth accompanied by an increase in wealth results in higher demand for construction timber, furniture, paper, and other forest products (Basnyat, 2009; Ince, Kramp, Skog, Spelter, & Wear, 2011). Despite the economic downturn, which substantially reduced timber output during 2008 and 2009, the U.S. continues as the world's leading consumer and producer of industrial roundwood and pulp for paper (FAO, 2010). At the same time, the demand for development land continues to threaten the sustainability of forests, as tracts of forestland are subdivided and sold for development (Mehmood & Zhang, 2001; Sampson & DeCoster, 2000; Stein et al., 2005). Sustainable management without sufficient focus on timber management could lead to future dependency on imported forest products, job losses, and probable damage to the rural economies.

Aside from the added demand for wood products posed by population growth, forests also face increasing health problems. The probable sources for these health problems range from air pollution and weather changes (Côté & Ouimet, 1996; Fettig et al., 2007) to increasing globalization and the associated unintentional transfer of invasive plants and organisms (Schoettle & Sniezko, 2007). In most instances, adequate forest management promoting tree vigor can limit the damage or avoid the onset of pests and diseases (Côté & Ouimet, 1996). The composition and structure of a forest plays a role in the forest's susceptibility to certain pests (Schoettle & Sniezko, 2007). Trees in an overstocked forest, for example, are stressed by natural competition that reduces the tree's ability to resist pests and diseases. Therefore, thinning can ensure adequate site capacity, resulting in stronger residual trees (Fettig et al., 2007) with better chances of defending against insects or pathogens. Single species, even-aged forest stands are generally considered more prone to diseases and pests outbreaks (Côté & Ouimet, 1996). Managing for mixed species, multi-age forests can then increase resistance to these disturbances (Samman & Logan, 2000). Management interventions however, carry costs that landowners might not be able to offset if, for instance, the demand for timber is weak or if the forestland owner's objectives do not include timber production.

Forest economists and other social scientists have dedicated considerable effort to understand the potential timber supply from private forest landowners (PFLs). Most of the previous research has been focused on the willingness of landowners to sell timber. A question, so far unanswered in the literature, involves the effect of primary wood-using mills on the likelihood of management activities by PFLs. The proposed research takes a new approach to the supply problem by using production data from primary wood-using mill surveys to analyze the role that mills play in shaping PFLs management activities within the procurement areas. Additionally, forest management planning requires information on expected wood demand. Although multiple models currently project timber requirements, the existing models inform large geographic areas, leaving the question of micro areas unsolved. Therefore, we present a study examining available time series of timber product output at the county level, to both evaluate a forecasting technique and to assess the behavior of these series.

Results from these studies should prove useful to industry and federal and state agencies alike, by identifying the interaction between primary wood processing plants and the timberlands that supply them. Such information can determine the expected response from landowners to increases or decreases in timber demand. Furthermore, policymakers can benefit from local information that indicates how primary wood processing plants influence timberland management in their procurement zones. Additionally, the ability to forecast short-term wood demand using information from the USDA Forest Service mill surveys provides a useful tool for policymakers and state foresters seeking to develop more effective programs.

2. Objectives

The objectives of the study are to (1) assess how proximity to a primary wood-processing mill affects the likelihood of forest management activities, and (2) examine the use of wood procurement and macroeconomic time series to forecast wood flow at the county level.

The research is organized as two individual studies using econometric methods for empirical analysis. The chapters begin with an introduction to the topic followed by a review of previous research. Each chapter includes a detailed discussion of methodology, results, and analysis. A separate chapter presents the overall conclusions, policy implications, and future research needs. Taken together, these studies describe the interaction between primary wood-using plants and the characteristics of the plants' procurement zone in an effort to understand the effect on supply.

3. The USDA Forest Service Forest Inventory and Timber Products Output Data

The national forest inventory program can track its origins to the McSweeney-McNary Forest Research Act of 1928 (P.L. 70-466). This Act authorized the USDA Forest Service to carry out the forest inventory to measure the nation's needs for timber and other forest products (Woudenberg et al., 2010). The inventory is carried out by the Forest Service Forest Inventory and Analysis (FIA) program. Although at that time the motivation for the inventory was primarily to evaluate the timber resources, this focus has shifted to include a broader set of objectives. The national forest inventory, currently authorized under the 1978 Forest and

Rangeland Renewable Planning Research Act (P.L 95-307) and amendments, includes a wider set of objectives. Current motivation for the inventory include the need to assess the status and trends of all natural resources, as well as, the need to evaluate the forests use and health (Woudenberg et al., 2010). This change in focus results from an increased knowledge of the multiple benefits forest ecosystems provide, as well as growing demands for non-timber products and services. The increase in globalization and resulting spread of pests and invasive species, place new demands on the Forest Service's forest inventory to assess the health status of the forests in the nation.

The FIA is currently organized into 4 regional units. Data collection takes place across the nation, but the responsibility for collection and reporting resides within each regional unit. Although part of the same program, the forest inventory and the mill survey operate under separate sections. Given the different nature of the data collected by these two sections, the methodology and survey design differ as well.

A. Forest Inventory (FIA) Data

To carry out the inventory, FIA established permanent plots within a continuous hexagonal grid across the country (approximately 1 plot every 6,000 acres). The first step in the inventory process involves classifying each plot into forest and non-forest categories using aerial photos or satellite imagery. Following this classification, field crews visit the plots and collect the ground information. Until recently, the FIA conducted periodic inventories, collecting the measurements for an entire state over a number of years. The amount of time, or period length, taken to complete each inventory ranged from five to ten years depending on the State. During 1999 the inventory changed from a periodic to an annual basis, where a portion of the plots are measured every year. This change in periodicity originated in response to the 1998 Farm Bill (P.L. 105-185) mandate for more recent information and increased frequency of reporting of forest inventory information (Gillespie, 1999). Additionally, during the mid-1990s the FIA adopted a national plot design to standardize the national inventory. This new design involves the use of a fixed instead of a variable plot radius (Woudenberg et al., 2010). For cases where the analysis applies to multiple states the difference in design can be a problem. Within the proposed study region, Florida is the only state that implemented a variable radius plot design. An additional caveat when using inventory estimates relates to the size of the analysis area. The error associated with the inventory estimates increases as the area decreases. For example, while estimates for a state might fall below the two percent sampling error, estimates for a small county within that state could have double-digit sampling error (Woudenberg et al., 2010). For this reason FIA does not recommend using data disaggregated at a level below the FIA survey unit (aggregation of counties sharing similar ecological characteristics within a state). Another alternative for analysis, and the one used in the empirical analysis presented in Chapter II, entails the use of the FIA plot level, instead of the county, as the observational unit.

B. The Timber Products Output (TPO) Data

The FIA timber products output program conducts periodic canvasses of primary wood-using mills in each state. As with the FIA forest inventory, each FIA regional unit manages the TPO for a set of states. Within the Southern region the TPO program currently carries out a mill canvass every two years for mills other than pulp mills, which are canvased annually. This bi-annual canvassing approach started in 1995. Previous to the bi-annual data collecting frequency, the TPO collected data as requested by each state. This as-needed data collection scheme resulted in uneven data years across states. Therefore, the TPO data provide an unbalanced panel for non-pulp mill. The TPO survey contains varied mill information: the mill's location, the counties each mill procured timber from, the total timber receipts per product type, and the tree species group utilized. In the following studies we utilize data from sawmills, veneer and plywood mills, pulp mills, and composite panel mills.

Although questionnaires are sent to all primary-wood using mills in each state, not all mills respond. It is possible that non-response occurs non-randomly and that, in fact, it identifies a certain type of mill owner. When the missing observations generate from a non-random process using the sample will result in inconsistent estimates for the population (Wooldridge, 2002). Currently, information identifying the rate of response is not readily available. Nonetheless, non-respondents include smaller mills which usually operate sporadically and account for a minor segment of the overall wood procurement (Johnson, 2011). On the other hand, there is a 100 percent response rate among pulp mills. The empirical analysis in the first study uses TPO data for South Carolina mills, which displays a 100 percent response rate (Steppleton, 2011).

II Evaluating the Effect of Available Mill Capacity on the Likelihood of Forest Management Activities

1. Abstract

As holders of a large portion of the timberland, and providers of the majority of the timber harvest in the South, PFLs harvest and regeneration choices can significantly impact forest sustainability in the region. The following essay examined PFLs harvest and regeneration responses to roundwood demand from primary wood-using mills using multivariate probit regression. The analysis utilized forest inventory and primary mill survey data from the USDA Forest Service Forest Inventory and Analysis Program for South Carolina, from 1999 to 2006. The regression allows joint estimation of the regeneration and harvest choices to assess the probability of regeneration on harvested stands. Results revealed a weak response to mill proximity, particularly for regeneration efforts. The results suggest the need for tools other than timber markets to ensure continued PFLs regeneration efforts.

2. Introduction

The United States is the world's leading producer of industrial roundwood (FAO, 2010), a leadership likely to continue into the future given the nation's abundant forest resources. Forests in the U.S. occupy one-third of the nation's total land area, constituting the fourth largest forestland base in the world (FAO, 2010). Additionally, more than two-thirds of U.S. forests are classified as productive forestland, or timberland, with 40 percent of the timberland and one-third of the growing stock volume located in the Southern region (Smith et al., 2009). Further, the South accounts for a significant portion of the total timber production. During 2009 this region provided 62 percent of the nation's total timber harvest (Smith et al., 2009). Combined, timberland area, high site productivity and significant mill capacity, point to continued reliance on the Southern region to meet the nation's timber needs.

Although timber resources and mill capacity exists, sustainable timber production from the South depends on the likelihood of PFLs to invest in forest management. The behavior of PFLs can significantly impact forest sustainability because they own the majority of the southern timberland, 58 percent in 2007 (Butler, 2008), and provide the majority of roundwood output, approximately 70 percent in 2007 (Johnson, Bentley, & Howell, 2009). Compared to industrial and corporate private forest owners, PFLs hold land for multiple reasons, often with no interest in timber production (Butler, 2008). In general, corporate and industrial timberland owners manage their lands to maximize profits (Hyberg & Holthausen, 1989). Private forest landowners, on the other hand, behave as utility- maximizing agents (Hyberg & Holthausen, 1989). As such, PFLs manage for timber and non-timber uses based on personal preferences. The degree to which PFLs manage for timber production depends on the level of utility received from the non-timber values of their lands (Dennis, 1989; Hyberg & Holthausen, 1989). In other words, the higher the preference for non-timber values, the less likely the management for timber production.

The issue of uncertain forest management on PFL tracts goes beyond future availability of timber, however, since active forest management also affects non-timber attributes - forest management can improve wildlife habitat or control invasive species. Likewise, forest management plays a role in forest protection. Thinning to lower stand density, for example, reduces the risk of forest fires by decreasing fuel levels. Similarly, thinning overstocked stands improves the forest stand’s overall health by easing the stress on the remaining trees (Fettig et al., 2007). Thus, the benefits of these interventions extend beyond timber production. However, the costs associated with management activities likely deter some PFLs from actively managing their forests.

Provided wood markets exist, the costs from thinning interventions can generally be offset with the sale of harvested roundwood. Costs from non-timber producing interventions (e.g. planting, or herbicide application) however, might be recovered in the long term by gains in timber growth. According to the U.S. Forest Service national woodland owners survey (NWOS), the majority of PFLs hold land for purposes other than timber production (Butler, 2008). In effect, the NWOS found PFLs' top reasons for owning forestland include aesthetics, family legacy, and privacy (Butler, 2008). If future timber harvest is not the owner's objectives, then investing in these interventions seems less likely. Nonetheless, studies have revealed that PFLs respond to prices, selling timber when the price is right (Cleaves & Bennett, 1995; Thompson & Jones, 1981). PFLs reservation price, however, may be higher than that of other private ownerships. Nonetheless, increases in wood demand, as reflected by higher stumpage prices, should motivate PFLs to invest in management to capture future expected returns from wood sales. Previous studies on the response of PFLs to price signals prove inconclusive (Dennis, 1990, 1991; Hyberg & Holthausen, 1989), with a number of studies finding stumpage prices not significant to the management decision (Beach, Pattanayak, Yang, Murray, & Abt, 2005). In general, researchers do not observe the stumpage price at the stand level. Instead, studies make use of regionally aggregated average prices. This data limitation likely contributes to the ambiguous results of price effects. Dennis (1990) points to measurement error that could arise from using a price index as a proxy for real stumpage price as a possible reason for the ambiguity of his results.

The research presented in this chapter examines the question of expected forest management by PFLs, given sustained demand from primary mills. As a complement to stumpage prices, the analysis incorporates TPO information to determine primary wood-using mill procurement influence for each FIA forested plot (with PFL ownership) in South Carolina. In this manner, the analysis examines the effect of mill demand on forest management, with mill demand measured by the stumpage price weighted by the volume of receipts per mill product type and by the number of mills in the vicinity of each plot.

3. Literature Review

Forests provide multiple benefits to timberland owners and society. These benefits result from standing timber and roundwood harvesting. Standing timber provides non-market amenities, as well as income possibilities arising from new markets such as ecosystem services and carbon markets. Harvested roundwood, on the other hand, provides a source of income to timberland owners and material supply to the timber industry, directly affecting the economies of rural communities. The sustainability of timber and non-timber services depends on the degree of forest management practiced by timberland owners. Management interventions include forest regeneration (natural or artificial), timber harvest (partial or total), and other activities to improve the stand (e.g. fertilizing, herbicide applications, and pruning). Forest management interventions are designed to produce and maintain desired forest characteristics such as species composition or stand structure. Most of these interventions do not produce immediate results, however, but change the forest conditions over time. Therefore, the objectives of timberland ownership play a central role in the likelihood of a landowner engaging in any managerial activities. Furthermore, sustainability of PFLs timberlands can significantly impact the future supply of timber and non-timber services. Consequently, considerable research has been conducted to understand the conditions under which PFLs engage in management activities. Beach et al. (2005) provides a comprehensive review of the research in this area. The most studied management activities include the likelihood of timber production, and the expected degree of regeneration investment (Beach et al., 2005; Cubbage, Snider, Abt, & Moulton, 2003).

A. Timber Production

Previous research reveals that multiple factors influence PFL decisions to sell timber. These factors include owner characteristics such as income, education (Dennis, 1989, 1990; Hyberg & Holthausen, 1989; Joshi & Arano, 2009) and age (Joshi & Arano, 2009; Kuuluvainen, Karppinen, & Ovaskainen, 1996); characteristics of the timber tract, including size (Boyd, 1984; Hyberg & Holthausen, 1989; Joshi & Arano, 2009; Kuuluvainen & Salo, 1991), accessibility (May & LeDoux, 1992) and location in relation to urban areas (Joshi & Arano, 2009); the characteristics of the forest resource, such as species composition and site productivity; and to some degree, timber prices (Boyd, 1984; Hyberg & Holthausen, 1989; Newman & Wear, 1993) and investment rate of return (Kuuluvainen & Salo, 1991).

The likelihood of timber harvest by PFLs relates directly to the size of their timberland, with owners of small tracts (under 50 acres) less likely to harvest timber. (Cleaves & Bennett, 1995; Hyberg & Holthausen, 1989; Thompson & Jones, 1981; Vokoun, Amacher, & Wear, 2006). However, even small tract landowners sell timber at some point (Cleaves & Bennett, 1995; Thompson & Jones, 1981). Small tract PFLs, however, reported sales primarily from thinning operations instead of clear cutting (Cleaves & Bennett, 1995). Additionally, the fixed costs associated with logging operations make harvesting small tracts more costly on a per-acre basis.

A survey of loggers in South Carolina revealed that only 15 percent of loggers were willing to harvest tracts under 10 acres (Moldenhauer & Bolding, 2009).

Accessibility plays an important role in the likelihood of harvest, as a timber tract with limited accessibility will incur greater harvesting costs. Factors determining tract accessibility include terrain conditions, road infrastructure, and distance to the mills. Steep terrain causes higher timber extraction costs due to the added time required to harvest the area. Likewise, the available class of roads and distance to the mills will affect transportation costs (May & LeDoux, 1992). More accessible timber tracts form part of preferred procurement areas. In contrast, timberlands with accessibility constraints require better-quality timber to compensate for higher harvest or transportation costs (May & LeDoux, 1992).

Other factors affecting the availability of timber from a timber tract include urban expansion and population density (Kline, Azuma, & Alig, 2004; Munn, Barlow, Evans, & Cleaves, 2002; Wear, Liu, Foreman, & Sheffield, 1999; Wear & Newman, 2004). As population grows and urban boundaries expand, the value of the land in the new urban boundary increases (Wear & Newman, 2004). Likewise, property taxes are generally lower in rural areas, making forest activities more costly near urban centers (Wear & Newman, 2004). Demand for residential and commercial space increases as population grows, contributing to forest fragmentation and encouraging timberland owners to harvest and sell the land for development (Wear & Newman, 2004). Fragmented patches are then less likely to be harvested due to increased harvesting costs (Dennis, 1990; Thompson & Jones, 1981; Wear et al., 1999; Wear & Newman, 2004).

Studies by Wear et al. (1999) and Munn et al. (2002) report an inverse relationship between population density and the likelihood of harvest. Wear et al. (1999) reported that for Virginia the probability of commercial timber harvest decreased as population density increased. The authors reported ranges from 25 percent probability of harvest for populations of 70 people per square mile (psm) to close to zero probability for populations of 150 psm and larger. This range represented an overall loss of about 40 percent of the timberland area and growing stock in the study area (Wear et al., 1999). Munn et al. (2002) examined harvesting decisions in the South-central states and concluded that higher population density reduces harvest levels up to 19 percent when population density increases from 10 to 170 psm. Additionally, the probability of harvest increases in areas at least 55 miles from the urban perimeter. The authors also found urbanization impacting specific timber products differently. In effect, pulpwood generated from intermediate timber harvest (harvest to improve stand growth) appeared more affected (lower volumes available) than saw-logs generated from final timber harvest (harvest where the entire stand is removed) (Munn et al., 2002).

Estimated supply elasticities for PFLs by Prestemon and Wear (2000) and Newman and Wear (1993) indicate them to be relatively inelastic. The level of elasticity varies between products, with saw-logs having relatively higher elasticities than pulpwood. In other words, timberland owners will be more responsive to changes in saw-log prices than pulpwood prices (Newman & Wear, 1993; Prestemon & Wear, 2000). Saw mills procure timber from the harvest of saw-log size stands. Wood chips for pulp mills, on the other hand, result from both pulpwood and residues from saw-logs harvest. Therefore, a price increase in saw-logs will correspond with an increase in both saw-logs and pulpwood supply (Prestemon & Wear, 2000).

Taking a different approach, Vokoun et al. (2006) analyzed PFLs responses to a set of price offers. The study determined the lower price and harvest intensity at which PFLs are willing to harvest. Vokoun et al. (2006) find that for a minimum acceptable price, the intensity of harvest varies according to ownership characteristics. Significant characteristics include timber-tract size, number of years owned, property as place of residence, and level of urban pressure measured by number of existing structures in the stand.

B. Regeneration Efforts

Unlike harvesting, forest regeneration is a long-term investment. Furthermore, costs from regeneration activities might prevent some owners from adequately stocking their lands. The lack of investment can result in stands with a less desirable mix of species, or in changes to land use. Forests provide an array of environmental services for public benefit, such as carbon storage, erosion control, and aesthetic quality. These social benefits, in part, justify the use of cost-share programs to ensure adequate forest regeneration in private lands. Two such programs in effect during the mid-70s and 80s include the Forest Incentives Program (FIP, 1978 to 2002) and the Conservation Reserve Program (CRP, 1985 to present). The Forest Incentives Program focused only on forestry activities, while in the CRP case tree planting is one of many objectives.

Under the FIP, cost-share covered up to 65 percent of the costs of reforestation and stand improvement for PFL lands (NRCS, 2009). However, planting was the largest management activity undertaken by PFLs, representing about 64 percent of the total acreage managed (Ellefson & Risbrudt, 1987). Brooks' (1985) simulation models of FIP effect on future supply and prices concluded that the cost-share program would in fact motivate PFLs to manage their forests. Similarly, Ellefson and Risbrudt's (1987) evaluation of the programs effect on timber yields concluded that sawtimber volumes in the South would experience the most benefits.

The CRP provides up to a 50 percent of cost-share for retiring marginal agricultural land for a specific contract period. The CRP aims at soil and water protection, as well as resource conservation (USDA Farm Service Agency, 2011b). Aside from planting cost-share, the program provides annual land rents per qualifying acre of land enrolled (USDA Farm Service Agency, 2011a). To be eligible, land has to have been in crop production for at least five years before the contract is awarded. Participation in the CRP is voluntary, and contracts are awarded through a competitive bidding process. As of August 2011, the program included 166,370 cumulative acres of tree plantings nation-wide, with 94 percent of those acres in the South. Across the Southern states, South Carolina ranks sixth in total planted acres and currently under CRP contract (USDA Farm Service Agency, 2011a). Contracts for tree planting are generally for 15 years.

Aside from cost share incentives, reforestation efforts by PFLs have been found to be positively correlated with landowner level of income (Li & Zhang, 2007), size of the timber stand (Zhang & Pearse, 1997), and stumpage prices (Hyberg & Holthausen, 1989; Li & Zhang, 2007).

C. Stand Improvement

Stand improvements (SI) include a range of forest management interventions performed as intermediate activities and intended to enhance forest characteristics such as timber growth, stand composition, or forest health. These activities, as regeneration, can be considered as an investment in forestland development. As such, stand improvement decisions are found to be affected by factors similar to those affecting the regeneration decision. Significant factors affecting PFLs' decisions to invest in SI activities include age and income, with younger landowners and those with higher incomes being more likely to invest in forest management (Romm, Tuazon, & Washburn, 1987). Previous studies find availability of cost-share regeneration programs playing a significant and positive role in the likelihood of observing SI activities on non-industrial forestlands (Boyd, 1984; Ovaskainen, Hänninen, Mikkola, & Lehtonen, 2006). Arano and Munn's (2006) study of PFLs in Mississippi found the volume of softwood (Romm et al., 1987) and the stand size as significant predictors in the likelihood of investment in intermediate forest management activities.

4. Landowner Management Decision

Forest management activities can be classified into three major groups; harvest, regeneration, and other timber stand improvement activities (e.g. herbicide application, non-commercial thinning, or pruning). A landowner faces different management intervention decisions at various points in the development of his or her forestland, with the type of management dependent on the forest characteristics. A rational landowner will conduct a particular forest activity (e.g. harvest or stand improvement) if the expected utility associated with this is greater than without intervention. Formally, let Y_{ij}^{*} denote the utility of management regime *j* to landowner *i*, where *j* =1 denotes the activity and 0 denotes otherwise. Further, assume that utility is a linear function of a vector, X_{ij}, comprising forestland attributes, timber markets, and costs associated with management interventions, plus an error component ε_{ij}, which represents components of utility unobserved by the analyst. This gives rise to the following relationship

$$Y_{ij}^* = X_{ij}\beta_{ij} + \varepsilon_{ij},$$

where ε_{ij} is assumed continuously distributed and independent of the variables in X_{ij}. Although utility is not directly observed, from the available data, we do observe whether a particular management regime was undertaken. Define the binary outcome Y_{ij}, where

$$Y_{ij} = \begin{cases} 1 \text{ if } Y_{ij}^* > 0 \\ 0 \text{ otherwise.} \end{cases}$$

Then, the probability of observing management j can be expressed as,

$$\begin{aligned} \text{Prob}(Y_j = 1 \mid X_j) &= \text{Prob}(X'\beta_j + \varepsilon_j > 0) \\ &= G(X'\beta) \end{aligned}$$

As the landowner can simultaneously choose none or all management activities, we specify a set of equations, assumed correlated though their errors, where the variables in X can vary across the different management choices. For a set of J forest management activities,

$$\begin{aligned} Y_1 &= G(X_1'\beta_1) \\ Y_2 &= G(X_2'\beta_2) \\ &. \\ &. \\ &. \\ Y_J &= G(X_J'\beta_J). \end{aligned}$$

Where $G(\cdot)$ is most commonly assumed to follow a normal (probit) or logistic (logit) distribution, although alternatives, such as the Weibull or log-log models, may instead apply (Green, 2003).

Given that consistent estimators for β rely on selecting an appropriate error distribution, the distributional assumption requires testing. Similarly, consistent estimation of binary models rests on the assumption of homoscedastic errors. Adding possible endogenous covariates further increases the complexity of estimation. Consistent estimation with endogenous regressors requires an assumption about the distribution of the endogenous variables, as well. Estimating the binary outcome model via a linear probability model (LPM) offers a way to circumvent the strong distributional assumptions needed for non-linear models. Additionally, with a LPM one can easily accommodate endogenous variables, as well as perform robust estimation of the errors under multiple forms of unspecified heteroskedasticity. However, although convenient for consistent estimation, the LPM fails to properly capture the nature of the binary outcome; for instance, by resulting in estimated probabilities outside the 0 to 1 range. Consistent estimation by LPM also carries the cost of efficiency loss, as the LPM is heteroskedastic by nature of the binary outcome (Green, 2003).

5. Empirical Application

We conducted an empirical analysis of the effect of mill demand on the likelihood of forest management using data for South Carolina. The USDA FIA forest inventory plot condition data provides the information for the dichotomous response variable. However, the sample of interest contains only plots classified as forestland and under non-industrial private ownership. The study used data from the two latest FIA forestry inventory cycles, covering 1999 to 2006. Additionally, FIA TPO program provided data on primary mill roundwood demand. These data were supplemented with information from other sources to control for exogenous factors hypothesized to affect the management decision. The sample included only plots with observations in both cycles. Reasons for a plot in the sample to appear in only one cycle vary, including a change in ownership type or land use status. These observations were dropped from the sample. With missing records removed, the sample includes 1,560 observations.

The plots stand size varies across the sample from plots located in stands with fewer than ten acres to plots in holdings with 1,000 acres and larger. Studies have revealed that stand size is a significant predictor of forest management, with 50 acres the usual minimum acreage needed to observe active management (Cleaves & Bennett, 1995). However, preliminary examination of the data revealed forest management activities in small stands, as seen in Table II-1.

A. *Study Area*

South Carolina has a total land area of 31,113 square miles, divided into 46 counties, with Horry county having the largest land area, and Greenville county the largest population center (US Census Bureau, 2011). Population growth estimates for 2010 place the state's growth rate close to 48 percent from 1980 to 2010, with the majority of the growth (84 percent of the overall increase) occurring in urban areas (USDA Economic Research Service, 2011).

According to the latest published FIA report, the 2006 volume of live trees on South Carolina's timberland totaled 21.5 billion cubic feet, with a net average total growth of over 1.2 billion cubic feet per year between 2002 and 2006 (Conner, Adams, Johnson, & Oswalt, 2009). For analysis purposes, FIA divides South Carolina into 3 sample units: Piedmont, Northern Coastal Plain and Southern Coastal Plain (Figure II.1); combining counties that share similar physiographic characteristics. Among these regions, the Southern Coastal Plain counties had the lowest percent of forestland, 26 percent, compared to 38 percent found in the Piedmont and 36

Table II-1 Outcome frequency by stand size categories.

Stand size	Total	Outcome = 0		Outcome = 1	
		Frequency	*Percent*	*Frequency*	*Percent*
Under 10	121	108	89.26	13	10.74
10 to 99	676	592	87.57	84	12.43
100 to 999	704	597	84.80	107	15.20
1000 & over	59	56	94.92	3	5.08
Total	1,560	1,353	86.73	207	13.27

Notes: Percent based on respective category total. Stand size in acres.

percent in the Northern Coastal Plain regions. In terms of species type, 46 percent of the state's forestland accounted for softwoods and 56 percent were hardwoods (Conner et al., 2009).

The majority of South Carolina's timberland is in private ownership, with PFLs the predominant group accounting for 7.3 million acres or 59 percent of the total timberland (Conner et al., 2009). Combined, forest industry and corporate owners hold 3.7 million acres (28 percent) with the remaining acres under state and federal ownership (Conner et al., 2009). The forest industry is an important component of the state's economy. Currently, the industry ranks second among the state's manufacturing sectors with an economic impact estimated at around $17 billion per year, supporting over 44,000 jobs (South Carolina Forestry Commission, 2011). Timber products output figures for 2007 indicate that 75 mills were operating in South Carolina during the year, with the majority of the production (87 percent) captured by pulp mills and sawmills (Johnson & Adams, 2009). Additionally, the majority of the roundwood volume originated from softwood species (81 percent). Most pulp mills operating in 2007 were located in the FIA Northern Coastal Plain unit, while all operating veneer mills were located in the Southern Coastal Plain unit. Although sawmills were scattered across the state, a larger number of small-size sawmills located in the Piedmont unit (Figure II.1).

B. Estimation Approach

Because plots are measured within a five to eight year cycle, a crew may record multiple management activities for one date even though the activities may have occurred through the cycle period. For instance, it is possible to observe vegetation control (stand improvement) together with harvest or regeneration. In some cases, field crews recorded the years in which

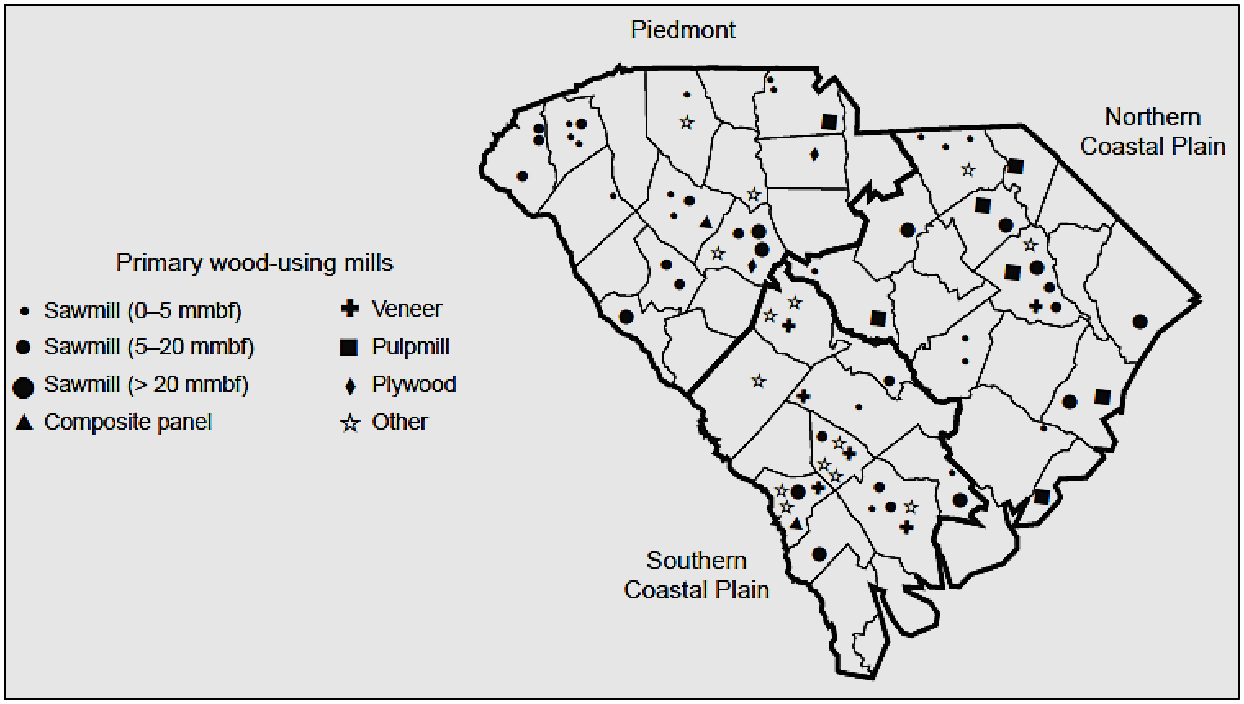


Figure II.1 Distribution of primary wood-using mills in South Carolina.
Source: Johnson and Adams (2009).

they estimated the different interventions occurred. While we assume that activities with an estimated date occurred in the estimated year, activities without a date were assumed to occur the year the crew collected the data. Furthermore, the plot volume recorded at the time of visit corresponds to the conditions at the time of the visit not the time of intervention. To estimate a plot's volume at a specific time of intervention, we fitted a regression estimating growth by species group using data from three inventory panels (1993 to 2006). Only plots with two or more consecutive observations without management interventions where included in the growth sample.

Given the binary nature of the response variables, a non-linear model seems appropriate. Although the distributions differ, in practice studies have found the probit and logit model offer similar results in terms of marginal effects (Green, 2003). We selected a probit model assuming normally distributed errors. The presence of suspected endogenous covariates, together with possible unspecified heteroskedasticity complicated the probit's estimation and the testing of theoretical assumptions. As a consequence, to explore the robustness of the results to theoretical assumptions, a linear probability model (LPM) for each management outcome was also estimated. Additionally, the specifications took into account that the dataset included two observations per plot, giving rise to correlation in plot-level unobservables. Consequently, we estimated cluster-robust standard errors.

For the analysis we used a multivariate probit regression to jointly estimate the set of binary choices associated with the selected forest management activities. Harvest can occur at different levels of intensity, from a clear cut to a partial or selective harvest. The FIA data provides information to distinguish between different types of harvest interventions. However, as seen in Table II-2, the relatively small number of positive outcomes by harvest intensity prevented the analysis at a disaggregated level. Likewise, FIA data allows disaggregating the regeneration into natural or artificial, and timber stand improvement information into thinning or other, but the disaggregated data presents a very low count of positive outcomes (Table II-2). Analysis with these low frequency events resulted in severe convergence problems. Therefore, the regeneration estimation only used the aggregated figures. As a reference, a probit regression using the timber stand improvement outcome was also estimated (Appendix A). Results from that estimation might be biased, however, due to the low representation of stand improvement positive outcomes (King & Zeng, 2001).

The data frequency allows disaggregating harvest at the species group level, however. Therefore, to examine the influence of species composition on likelihood of management, we disaggregated the harvest outcome by hardwood and softwood. Given the mixed species composition of most stands, one expects the hardwood and softwood harvest outcomes to be correlated. Additionally, regeneration is believed correlated with harvest. For instance, regeneration reflects the likelihood of maintaining the land in forest after harvest. Also, regeneration efforts to improve stand stock, composition, or quality suggest a correlation with future timber production. Consequently, these three outcomes where estimated jointly as a multivariate probit.

Estimating a multivariate probit using maximum likelihood is computationally difficult because of the multiple integrals involved. The simulated maximum likelihood (SML) method offers an alternative for estimation (Green, 2003). With the SML, the likelihood is approximated by using

Table II-2 Outcome frequency by management activity.

Activity	Outcome = 0		Outcome = 1	
	Frequency	*Percent*	*Frequency*	*Percent*
Harvest	1,381	88.53	179	11.47
By intensity				
Clearcut	1,484	95.13	76	4.87
Thinning	1,517	97.24	43	2.76
Partial harvest	1,502	96.28	58	3.72
Shelterwood	1,558	99.87	2	0.13
By species group				
Hardwood	1,434	91.92	126	8.08
Softwood	1,418	90.90	142	9.10
Regeneration	1,444	92.56	116	7.44
By type				
Natural	1,481	94.94	79	5.06
Artificial	1,523	97.63	37	2.37
Stand Improvement	1,514	97.05	46	2.95

Note: Percent based on a total 1,560 observations.

a number of pseudo random draws from the standard uniform distribution. The SML precision increases with the number of draws used. However, the efficiency of a large number of draws comes at the cost of processing time. The recommendation is to select a number that offers good precision. For the present analysis we used 500 draws, which was sufficiently large to provide precision to four decimals. We arrived at this precision estimate by comparing the coefficients between an MVP with 450 and one with 500 draws. Further, the selected number of draws falls within Cappellari and Jenkins (2003) recommendation to use at least √N draws for seed stability (with N=the number of observations), or 40 draws in our sample. For the analysis we used the default seed set by Stata.

In the multivariate probit, calculating the probabilities requires an additional simulation step. Using the results from the multivariate probit, the method involves drawing a set of simulated observations for each equation (Cappellari & Jenkins, 2006). Then, the probabilities can be estimated for any combination of the outcomes by specifying the outcomes' value of interest. After calculating the predicted probabilities one can estimate conditional probabilities to evaluate the interaction between management activities. The conditional probabilities were estimated using trivariate and bivariate predicted probabilities. Following the conditional probabilities rule, the probability of event A given events B and C is expressed as,

$$P(A \mid B \,\&\, C) = \frac{P(A \text{ and } B \text{ and } C)}{P(B \text{ and } C)}.$$

In this way, the conditional probability in the trivariate probit is,

$$P(M_1 = I_1 \mid M_2 = I_2 \text{ and } M_3 = I_3, X) = \frac{\Phi_3(X_1^{'}\beta_1, X_2^{'}\beta_2, X_3^{'}\beta_3, \Sigma)}{\Phi_2(X_2^{'}\beta_2, X_3^{'}\beta_3, \rho_{23})}.$$

Where M_j represents the management type (j=1, 2, or 3 - harvest of softwood, harvest of hardwood, and regeneration), and I_j is an indicator variable for management type j, equal to 1 if the outcome is positive and 0 otherwise. Φ_i is the joint standard normal distribution with i number of joint equations; Σ represents the correlation matrix across the three outcomes, and ρ_{23} denotes the correlation between the two conditioning outcomes.

To evaluate the magnitude of the independent variables effect on the probability of outcome success, we calculated the average marginal effect for the variables of interest. As a default, the marginal effects for the single probit and bivariate cases are reported at the average value of each variable. For multivariate cases with more than two equations, we used the estimated coefficients to estimate the marginal effects and then averaged the effect over the sample. The marginal effect for a variable x_j was found by estimating $\frac{\partial E[y/x]}{x_j} = \phi(x'\hat{\beta}_k)\hat{\beta}_{kj}$, using the estimated linear prediction, $(x'\hat{\beta}_k) = \hat{y}_k$, for outcome k and the estimated coefficient $\hat{\beta}_{kj}$ for the variable of interest x_j; where ϕ denotes the standard normal density function.

C. Variables and Data Sources

Based on the review of past research on roundwood supply and demand, the covariates hypothesized to influence management decisions provide information characterizing each observational unit (FIA plot) in terms of forest resource and owner attributes, plot location, and available wood markets. Table II-3 lists all included variables with respective data sources.

Table II-3 List of dependent variables with description, units, and data source.

Variable	Description	Units	Mean	Std. Dev.	Source
oper	Indicator = 1 if signs of timber equipment operability constrains	n/a	0.28	0.46	FIA
delta	Number of years between plot visits	units	5.51	2.12	FIA
lnstand	Size of stand in log form	ln(acres)	4.50	1.47	FIA
propswd	Proportion of softwood to total plot volume	1,000 cubic feet	0.48	0.39	FIA
miles_town	Distance from plot to nearest town	miles	6.59	4.51	FIA & US Census
ppsqm	Number of people per square mile	unit	132.67	113.83	US Census
percinc	Average per capita income	1,000 dollars	27.24	4.19	US Census
pop65	Percent of population 65 years and older	percent	12.76	1.81	US Census
unit2	Indicator =1 if SC Northern Coastal Plane survey unit	n/a	0.28	0.45	FIA
unit3	Indicator =1 if SC Piedmont survey unit	n/a	0.40	0.49	FIA
land_dac	Agricultural land value	$1,000/acre	2.61	1.11	US Census
acres_chg	Net change in total acres under cost share	acres	0.03	0.18	USDA,NRCS
gs01	Annual change in the one year interest rate treasury	unit	-0.16	1.55	FRED
whst	Weighted hardwood saw logs stumpage price	$/1,000 board feet	5.51	5.37	TMS & FIA, TPO
wsst	Weighted softwood saw logs stumpage price	$/1,000 board feet	10.81	11.33	TMS & FIA, TPO
wsply	Weighted softwood ply logs stumpage price	$/1,000 board feet	11.41	17.86	TMS & FIA, TPO
whpw	Weighted hardwood pulp logs and chips stumpage price	$/1,000 cords	1.05	1.66	TMS & FIA, TPO
wspw	Weighted softwood pulp logs and chips stumpage price	$/1,000 cords	1.74	1.96	TMS & FIA, TPO
hsaw70	Number of hardwood sawmills within 70 miles of plot *i*	units	3.05	2.34	FIA, TPO
ssaw70	Number of softwood sawmills within 70 miles of plot *i*	units	6.02	2.60	FIA, TPO
sply70	Number of softwood veneer and plywood within 70 miles of plot *i*	units	0.97	0.77	FIA, TPO
hpw100	Number of hardwood pulp and panel mills within 100 miles of plot *i*	units	1.38	0.71	FIA, TPO
spw100	Number of softwood pulp and panel mills within 100 miles of plot *i*	units	4.17	1.34	FIA, TPO

Forest resource and owner characteristics

Information on forest resource and plot characteristics includes the plot's volume of hardwood and softwood at each inventory. To capture the effect of species composition, species volume was measured as a proportion of the plot's total timber volume. In this manner, a plot volume corresponds to the proportion of softwood volume (*propswd*) in both the hardwood and softwood harvest specifications. Other plot characteristics included the size of the forest stand where the plot is located (*lnstand*), an indicator of operability constraints (*oper*) such as steep terrain or wet soil conditions, and the plot's distance to the nearest town (*miles_town*).

Previous studies suggest forestland owner age, level of education and exogenous income as primary determinants on likelihood of management (Joshi & Arano, 2009). Unfortunately, detailed owner information is not available at the plot level. An attempt to use data from the FIA National Woodland Owners Survey (NWOS) as a proxy resulted in high multicollinearity among the variables. The NWOS data provides a general characterization of plot owners. However, NWOS data are aggregated by FIA survey unit, which limits the information to three values for the state. Furthermore, only one cycle of the NWOS was available. Therefore, a plot was assigned the same value over the two inventory cycles. Consequently, the final model specifications did not include the NWOS variables.

Plot location

Variables to control for the effect of the plot location on the likelihood of management included general characteristics of population and infrastructure for a plot's county. Population variables included the population density as total number of people per square mile (*ppsqm*), the average per capita income (*percinc*), and the percent of people 65 year and older (*pop65*). We expect that per capita income and age will capture some of the information on owner characteristics, as well.

Wood market and demand availability

To control for the influence of mill demand on the management decision, we used two measures – the stumpage prices weighted by mill receipts, and the number of mills within a plot's supply area. The area from which a mill procures timber is given by the mill's average procurement distance, or procurement radius. In a similar manner, we estimated a supply area for each plot, given by a radius based on average mill procurement distance. All mills found within the plot's supply area formed the likely market for the plot's timber. A similar approach was used by White & Carver (2004) to determine the procurement influence for mapping cells. For saw mills and veneer mills we used a 70-mile radius, which is close to the average procurement distance observed in the sample, and falls close to average procurement distances reported in the literature (White & Carver, 2004). For panel and pulp mills we used a 100 miles radius, to accommodate the larger distances from which these mills procure wood.

Stumpage prices from Timber Mart South, TMS (Timber Mart-South, 2006) represent an aggregated average annual price, reported for two regions in the state. The analysis included stumpage prices for three primary products (saw timber, plywood and pulpwood) by major species group (hardwood and softwood) with the exception of plywood prices which are for softwood. To incorporate the volume of mill demand, each price was weighted by the total volume procured by a plot's county over the total volume procured from the plot's TMS's price region. Procurement volumes were calculated using TPO figures and included receipts from all mills drawing timber from a county. In other words, the volume includes procurement from in-state and out-of-state mills. For the case of hardwood saw-logs the price-weight included volume of receipts from sawmills and veneer mills combined. Likewise, pulpwood prices were weighted by the volume from pulp mills and panel mills combined. The five variables included hardwood pulpwood (*whpw*), hardwood sawtimber (*whst*), softwood pulpwood (*wspw*), softwood sawtimber (*wsst*), and softwood plywood (*wsply*). Information on mill receipts is available, mostly, over odd years. Missing data years were estimated via linear interpolation. A mill's volume was interpolated only if the mill showed receipts before and after the interpolated year, otherwise the volume of the even year was left as zero. For example, a mill reporting receipts in 1999 and 2001 will have an interpolated volume of receipts in 2000. A mill reporting receipts in 1999 but not in 2001 will have no volume for 2000.

In addition, the specification included a measure of market availability for each plot represented by the number of mills by product type within the plot's supply area. It was expected that a larger number of mills would result in a higher likelihood of management. Number of mills by mill type include the following categories- hardwood saw and veneer mills (*hsaw70*), hardwood pulp and panel mills (*hpw100*), softwood saw mills (*ssaw70*), softwood plywood mills (*sply70*), and softwood pulp and panel mills (*spw100*). For years without mill information, we followed a similar procedure as for the interpolated mill receipts, counting a mill in the missing year only if the mill was present before and after the missing year. Mills not operating in 1999 (the initial year of the analysis) were excluded from the plot supply area.

D. Specification Tests

As previously mentioned, consistent estimation relies on the validity of the model assumptions including the model's distributional assumption, homoskedasticity of the errors, and exogeneity of the covariates. We investigated the strength of these assumptions using standard tests, and report the results in Table II-4. Furthermore, before estimation, a Hausman test for fixed effects was performed. Using a pooled sample when fixed effects are present will render inconsistent estimates. To test for fixed effects, we used the Hausman test in the context of the LPM.

We tested the distributional assumption via a Lagrange multiplier test of the normality of the residuals from the estimated probit. Unfortunately, the test assumes homoskedasticity, and does not allow for robust cluster error estimation (Amadou, 2010).

The homoskedasticity assumption can be relaxed by explicitly including a form of heteroskedasticity in the probit specification. We follow the common approach and modeled the variance as a multiplicative function of a set of the independent variables *Z*, $\sigma = \exp(Z'\delta)$, with the resulting heteroskedastic probability expressed as

$$\text{Prob}(M = 1 \mid X) = \Phi\left(\frac{X'\beta}{\exp(Z'\delta)}\right).$$

In *Z*, we included two variables believed having the greatest effect in the heterogeneity of the data - stand size (in log form) and site index for hardwood species. Stand size captures the heterogeneity of the ownerships and has been shown to affect the likelihood of management (Hyberg & Holthausen, 1989; Prestemon & Wear, 2000) and be a significant variable in the identification of PFLs objectives (Majumdar, Teeter, & Butler, 2008). The site index for hardwood species indicates site quality within the area where a plot is located, providing information on tree growing potential.

Lastly, the exogeneity of plot volume and stumpage prices was also tested. In terms of plot volume, it was assumed that stands with a high volume of standing timber were more likely to be managed. Likewise, a managed forest is expected to yield higher volumes of timber. Therefore, establishing the cause and effect between management and stand volume proved difficult. Likewise, increases in stumpage prices are likely to increase harvest rates indicating likely endogeneity. For the analysis at hand, however, we expect the stumpage prices to be exogenous to the management decision. Stumpage prices are available aggregated into two regions for the state. Changes to the level of harvest experienced by one plot are unlikely to affect the average prices for an entire region. To investigate the exogeneity of these variables we used a set of instrumental variables and the Newey (1987) two-step robust estimation approach.

Instrumental variables selection

Variables expected to be correlated with a plot's timber volume include those likely to affect tree growth but which do not affect or are affected by management. Site index, which indicates site quality, is one such variable. The site index used originates from the USDA soil survey (NRCS, 2011) and includes two variables, a site index for softwoods (*index_s*) and one for hardwoods (*index_h*). Additionally, the instruments included a set of variables from the FIA plot condition table that describe the plot's potential to grow timber. Specifically, an indicator variable for physiological class equal to one if the site does not classify as mesic (*non_mesic*), and a set of indicator variables for the plot's estimated productivity class (*site_low, site_med, site_medh, and site_high*) were included. To avoid collinearity the indicator for *site_low* was excluded.

Instruments for the stumpage prices included variables that were correlated with price but exogenously determined. Specifically, the excluded instruments correlated with stumpage prices included logging prices by product type and major species group (*logg_hpw, logg hst, log_spw, and log_sst*), total number of logging operations by county (*loggers*), and average volume of rain by county and year (*rain*). The logging price variables obtained from the Timber Mart-South data (Timber Mart-South, 2006) likely affect levels of harvest and therefore prices. Similarly, a high number of logging operations in an area will result in more competition and likely higher stumpage prices. The information on number of logging operations comes from the U.S. Census Bureau. Lastly, the rain variable correlates with prices through timber accessibility. During a dry year, for instance, loggers can access timber more easily, causing subsequent decline in stumpage prices due to timber overflow.

6. Results and Discussion

Coefficients estimated by a probit model do not provide the magnitude of the effect. Instead, the signs of coefficients show the direction of the effect, while the usual t-test serves to indicate the coefficients' significance. To evaluate the size of the effect from significant coefficients one needs to calculate the marginal effects. The output table for the multivariate probit model (Table II.4) illustrates that most variables displayed similar signs across the two harvest equations (softwood and hardwood). A plot proportion of softwood volume (*propswd*) appeared as a

Table II-4 Multivariate probit regression, harvest by species group and regeneration outcomes.

	Equation 1		Equation 2		Equation 3	
Variables	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
delta	0.1916***	(0.036)	0.1533***	(0.034)	0.2656***	(0.056)
t	-0.1554***	(0.032)	-0.1747***	(0.033)	-0.2012***	(0.043)
oper	-0.1384	(0.123)	0.0078	(0.119)	-0.4063***	(0.134)
lnstand	-0.0097	(0.035)	-0.0182	(0.034)	0.0013	(0.034)
propswd	0.5432***	(0.134)	0.2576**	(0.120)		
gs01	-0.0015	(0.034)	0.0283	(0.033)	0.0643*	(0.037)
land_dac	-0.0000	(0.000)	-0.1000	(0.000)	-0.1000	(0.000)
miles_town	0.0097	(0.011)	-0.0020	(0.011)	-0.0117	(0.012)
ppsqm	-0.0013	(0.001)	-0.0021**	(0.001)	-0.0006	(0.001)
percinc	0.0354*	(0.021)	0.0347*	(0.021)	-0.0144	(0.024)
pop65	-0.0066	(0.037)	-0.0652*	(0.039)	-0.0213	(0.048)
unit2	-0.2734*	(0.165)	-0.3095**	(0.154)	0.0532	(0.159)
unit3	0.3070**	(0.142)	0.1891	(0.135)	0.0733	(0.160)
wsst	0.0061	(0.004)			0.0058	(0.005)
wsply	0.0006	(0.003)				
ssaw70	0.0323*	(0.019)			-0.0013	(0.026)
sply70	-0.0610	(0.065)				
spw100	0.0559	(0.040)				
hsaw70			0.0579**	(0.026)	-0.0266	(0.035)
hpw100			0.0506	(0.062)	0.0582	(0.074)
whst			0.0015	(0.013)	0.0402***	(0.016)
whpw			-0.0026	(0.031)		
low_site					0.0591	(0.212)
med_site					0.3092**	(0.158)
medh_site					0.3690**	(0.157)
acres_chg					-0.1613	(0.254)
Constant	-3.4711***	(0.726)	-1.8428***	(0.632)	-1.9527**	(0.835)
rho21	0.8645***	(0.027)				
rho31	0.7631***	(0.039)				
rho32	0.7935***	(0.036)				
Log Pseudo-likelihood		-861.109				
Draws		500				
Observations		1,560				

Notes: Equations 1= softwood harvest, 2= hardwood harvest and 3= regeneration.
Standard errors adjusted for 780 clusters in plot id.
***=1% significance, **=5% significance, and *=10% significance.
Likelihood ratio test of rho21 = rho31 = rho32 = 0: $\chi^2(3)$ =440.61; Prob > χ^2 = 0.0000.

significant predictor in both equations, and displayed a positive sign indicating a higher likelihood of harvest with increased proportion of softwood species.

As previously mentioned, the majority of the wood output in South Carolina originates from softwood species, comprising 87 percent of the total output in 2007 (Johnson & Adams, 2009). Therefore, an increase in plot softwood volume likely increases the probability of harvest. With only a few exceptions, all other covariates in the harvest equations (equations one and two) yielded the expected signs, although many were not statistically significant. Among the variables of interest (market variables), only the number of sawmills proved statistically significant to harvest. The number of softwood sawmills (*ssaw70*) was significant to the softwood harvest (equation one) at the 10 percent level. The number of hardwood sawmills (*hsaw70*) was significant at the five percent level in the hardwood harvest equation.

Sawmills are an important source for pulp material, both directly and indirectly. Harvest of roundwood pulp most often results as a bi-product in the harvest of saw-log size timber (e.g. smaller logs, tops and branches), as opposed to harvest of small size stands. Additionally, pulp and composite panel mills secure a portion of their raw materials from sawmill and veneer mills residues. Consequently, the influence of sawmills to the harvest decision carry implications for future supply of pulp using mills, as well. For instance, a drop in number of operating sawmills, assuming an associated fall in production, will result in less harvest of saw-log size stand which in turn will reduce the volume available to mills using pulpwood. In the short term, with the demand of pulpwood constant, the reduction in pulp material from less saw-log harvest will likely motivate intermediate harvests (thinning) creating an opportunity for landowners to reduce stand density while increasing potential growth for remaining trees. In the long-term, a sustained drop in saw-log harvest could lead to overabundance of large size timber with consequent declines in saw-log prices.

Most covariates in the regeneration equation displayed the expected signs. Variables controlling for site quality were all positive and significant, but the variable controlling for the effect of cost share of regeneration (*acres_chg*) was not statistically significant. Also unexpected was the positive effect of the short term interest rate (*gs01*) on regeneration, which significant at the 10 percent level. When considering the interest rate as an indicator of returns from alternative investments, one expects a negative effect on regeneration. Higher rates make alternative investments more attractive. The presence of a positive effect could be attributed to the positive influence of short-term interest rates on available exogenous income (Dennis, 1991). The effect might also reflect the likelihood to invest in regeneration when alternative investments offer low returns. Only the price of hardwood saw-logs was statistically significant among stumpage prices in equation three (regeneration). As for the number of mills, none emerged as statistically significant to the regeneration decision.

Jointly estimating the regeneration and harvest outcomes resulted in a significant and positive correlation across equations. The correlation between hardwood and softwood harvest (equations one and two) was slightly higher with ρ_{12}=0.86 compared with regeneration-hardwood harvest (equations two and three) ρ_{32}=0.79 and regeneration-softwood harvest (equations one and three) ρ_{31}=0.76. These correlations signaled a strong positive dependency between the errors. Consequently, unobserved factors influencing the likelihood of harvest of one species group increase the probability of harvest for the other species group, and the likelihood of regeneration as well.

Table II-5 lists the multivariate probit predicted probabilities for all outcome combinations. Considering the low frequency of positive outcomes, the probabilities were as expected. The highest probability of a positive outcome occurred for the combined outcomes, P(111), with only 3.20 percent compared to the probability of observing no management, P(000), which was close to 86 percent. The probability of softwood harvest as the only positive outcome observed, or P(100), ranked second with 2.63 percent probability.

Table II-6 presents the results from the average marginal effect for variables of interest (significant market variables as well as plot volume variables). Among the significant variables across harvest outcome equations, the plot proportion of softwood species yielded the largest effect. A one percent increase in a plot's proportion of softwood would increase the probability of softwood harvest by 7.22 percent and the likelihood of hardwood harvest by 3.26 percent. Plots with a higher proportion of hardwoods might be less likely to be harvested given the lower demand for hardwood roundwood. In comparison, the significant market variables showed lower effects. The addition of one hardwood sawmill would increase the probability of hardwood harvest by 0.73 percent, while adding one more sawmill using softwood increase the probability of softwood harvest by less than half of a percent (0.43 percent). For regeneration, a one dollar increase in the expected stumpage price of hardwood saw-logs would increase the likelihood of regeneration by 0.5 percent. Likewise, an increase in the one year interest rate would increase the probability of regeneration by 0.73 percent.

Table II-5 Multivariate probit predicted probabilities.

P(*ijk*)	Probability	Standard error
P(000)	0.8632	0.00317
P(111)	0.0320	0.00093
P(100)	0.0263	0.00072
P(110)	0.0171	0.00054
P(101)	0.0111	0.00036
P(011)	0.0094	0.00031
P(010)	0.0199	0.00047
P(001)	0.0210	0.00076

Notes: *i*= harvest softwood, *j*= harvest hardwood, and *k*= regeneration.

Table II-6 Average marginal effect on the marginal probabilities of harvest & regeneration.

Variable	Description	Harvest softwood	Harvest hardwood	Regeneration
propswd	Plot proportion of softwood	0.0722 (0.0015)	0.0326 (0.0007)	
ssaw70	Number of softwood sawmills	0.0043 (0.0001)		
hsaw70	Number of hardwood sawmills		0.0073 (0.0001)	
whsw	Weighted stumpage price, saw-logs			0.0046 (0.0001)
gs01	Interest rate			0.0073 (0.0002)

Note: Standard errors in parenthesis.

Evaluating conditional probabilities provided a view of the interactions across the harvest-regeneration outcomes (Table II-7). As such, plots with harvest of both hardwood and softwood had a 58.14 percent probability of regeneration. The probability dropped significantly when the harvest involved a single species, with harvest of hardwood showing the larger probability of regeneration at 37.13 percent. Observing regeneration when no harvest had occurred carried a low probability (2.37 percent), implying that if regeneration occurred, it took place for the most part, in relatively close proximity to the harvest event.

The robustness of the estimation was assessed via a set of tests. Because we have repeated observations per unit, we used a Hausman test to determine the presence of unobserved individual effects correlated with the error term (fixed effect). Results strongly supported the null hypothesis in favor of pooled estimation for harvest (hardwood p=0.5984 and softwood p=0.9966) and regeneration (p=0.9370). Normality and homoscedasticity were tested using single probits (outputs found in appendix A) instead of the multivariate probit. The results, found in the appendix Table A-1, support the normality and homoscedasticity assumptions for the singular probits. Although not conclusive, the results suggest the assumptions holding for the multivariate probit as well. Lastly, Wald tests confirmed the exogeneity of the variables suspected endogenous. As further verification, we tested these assumptions using the LMP and found similar results.

Table II-7 Conditional probability of regeneration, multivariate probit.

Conditional outcome	Probability
Pr(rg=1|hs=1, hh=1, x)	0.5814
Pr(rg=1|hs=1, hh=0, x)	0.3247
Pr(rg=1|hs=0, hh=1, x)	0.3713
Pr(rg=1|hs=0, hh=0, x)	0.0237

Notes: rg= regeneration; hs=softwood harvest; hh=hardwood harvest.

7. Conclusions

The study evaluated the influence of mill presence in the likelihood of PFLs to manage (harvest or regenerate) their timberlands. We expanded on previous research by incorporating additional information capturing wood demand. Namely, we utilized figures from primary mill wood receipts, as well as, mill location relative to forested plots. Results from this research will prove useful to policy makers by providing further insight about the likely influence of wood processing plants on PFLs timberland management. Further, the analysis contributes information about landowners' expected response to regeneration and harvest activities under varying levels of market potential as measured by the number of mills in proximity to a plot. This information may prove useful to industry and state foresters when dealing with increases in demand arising from new markets, such as bioenergy. Furthermore, investigating to what extent mill demand affects forest management activities provides new facts to assist landscape policy management addressing joint production of timber and non-timber benefits.

Empirical analysis using data from South Carolina corroborated previous findings of PFLs' weak response to stumpage prices (Dennis, 1989, 1990; Kuuluvainen et al., 1996; Prestemon & Wear, 2000). The results revealed that contrary to common belief, the presence of a mill affected the management decision only marginally. In fact, sawmills were the only mill type that exhibited a significant, although small, effect in the probability of harvest throughout the specifications.

Sawmills play a significant role in the procurement of raw materials to pulp using mills, both directly, through the supply of mill residues, and indirectly through the associated pulpwood volume obtained during saw-log harvesting. Given this relationship, the significance of sawmill proximity on the likelihood of harvest affects pulp production as well. The diminishing numbers of sawmills, for example, could negatively affect the supply of nearby pulp using mills, at least in the short term. A loss of sawmills could also increase the harvest of young stands, or motivate the harvest of saw-log timber to satisfy the pulp demand. Further research could explore the relationship between these two products and the likelihood of PFLs to substitute between them. Merging the FIA forest inventory with the TPO data offers the ability to explore this and other questions that might lead to a better understanding of the role that primary mills play in the management of our forestlands.

Forest management is needed not only to supply industry and satisfy our needs for wood products, but also to reduce forest health risks and ensure continuity of the many non-timber benefits forests provide. Given that wood markets seem to affect management decisions only slightly, exploring the use of mechanisms other than timber production is needed. One such mechanism may include policies promoting payment for ecosystem services, perhaps in the form of management agreements to provide PFLs with either annual rents or tax deductions.

Regeneration efforts play a central role in forests continuity. The analysis findings point to a moderate probability of regeneration (close to 58 percent) after observing harvest of mixed species, and much lower probabilities (37 percent in hardwoods and 32 percent in softwood) after harvest of a single species group. Further research may look into existing regeneration patterns and explore new means to help achieve higher rates of regeneration after harvest. Similarly, results suggest forest composition as an indicator of likely management. A positive response to management resulted with increased proportion of softwood volume which corresponds with the wood market preference for softwood species, and the assumption of hardwood species as indicators of PFL preferences.

The analysis introduced the use of a market area to study the effect of mill demand on a given FIA plot. This market, or plot supply, area was based on an average mill procurement distance. Expanding the concept to compare responses to different procurement distances could provide further insight into the relationship between observed management and mill presence. Expanding the dataset to include multiple states, as well as, additional inventory data would certainly strengthen any conclusions, as well.

III Forecasting County Pulpwood Harvest Using Macroeconomic Conditions

1. Abstract

The following study investigated the use of vector autoregressive (VAR) models to forecast the volume of pulpwood output at the county level. The research explored the ability to forecast using a set of vector autoregressive specifications including a standard VAR, a factor-augmented vector autoregressive (FAVAR) and a panel VAR model (PVAR). We used pulpwood output information collected by the USDA Forest Service Forest Inventory and Analysis Timber Products Output for Florida, together with national Gross Domestic Product (GDP) and Producer Price Index (PPI) information for pulp and paper products. Forecasting tools offer planning information useful to forest managers and mill procurement agents. Our forecast analysis utilized publicly available data and methodologies that can be replicated in most software packages. Although the accuracy of forecasts varied across counties, in general the VAR forecasting accuracy proved relatively low. Comparing the different VAR methods to a simple step-forward forecast, however, revealed cases with significant gains, where one or more of the VAR specifications reduced the forecast error of the step-forward forecast by over 50 percent. Results support the need for analysis with disaggregated data to better capture the dynamics across counties in a procurement area.

2. Introduction

Planning management activities to support sustainable timber harvests requires, among other things, an understanding of the relationship between timber supply and demand (Daniels & Hyde, 1986; Jackson, 1983). Considerable research addresses expected future timber demand, as well as conditions for likely timber supply. However, most supply-demand econometric models focus on long-term equilibrium analysis for the entire sector, and over large geographic regions (Buongiorno, Kang, & Connaughton, 1988; Sohngen & Sedjo, 1998).

Although these large-scale, long-term equilibrium models identify factors affecting the production process, they cannot be applied to smaller areas without added uncertainty and error (Buongiorno et al., 1988; Jackson, 1983). Nonetheless, a need exists for disaggregated short-term models. Transportation costs constrain primary wood-using mills to localized markets, justifying the need for small scale supply and demand models. At the same time, increasing globalization of the forest sector triggers a need for short-term forecasting to capture the effect from swift changes resulting from changing macroeconomic conditions (Hetemäki, Hanninen, & Toppinen, 2004; Malaty, Toppinen, & Viitanen, 2007). Developing econometric models for small areas such as individual counties or mill procurement zones, however, requires disaggregated data that can prove difficult and expensive to obtain. Consequently, this chapter explores the use of VAR models as an alternative to an econometric supply-demand model, avoiding the need for disaggregated data. Specifically, we evaluated the forecast of county pulpwood production among a set of specifications, including a simple vector autoregressive model with exogenous variables (VAR) and a VAR with factor variables (FAVAR). Additionally, we combine all counties to assess the accuracy of a panel VAR (PVAR) forecasts.

Economic growth is an indicator of timber product demand. Positive economic conditions, particularly those related to housing, result in increased consumer spending on wood products. As the demand for end-use wood products changes, the volume of roundwood demand will shift accordingly. The endogenous variables considered include roundwood volume procured from each county in the study area, U.S. GDP, PPI for pulp and paper products, and the U.S.-Canada exchange rate.

Short-term forecasts similar to the proposed project currently originate from forest sector consultants and analysts using ad-hoc methods or poorly documented assumptions (Hetemäki et al., 2004; Hetemäki & Mikkola, 2005). The forecast analysis developed in the following sections contributes documented methods for forecasting tools in the VAR family using public data, which can be easily replicated. Further, a forecasting practice commonly used by TPO involves using past data to represent current missing information. By comparing the performance of other forecasting methods to this step-forward ad-hoc methodology, this research could guide future TPO data management. The research also will assess the existence of procurement hot spots (counties expected to supply higher levels of roundwood). Without adequate forest management, counties under high procurement demand will likely experience difficulties with continued roundwood supply. Therefore, identifying these areas will prove useful to forests managers and timberland owners in planning forest management activities. Additionally, such forecasts offer valuable projections to timber mills in planning timber procurement, and to state extension foresters in directing management efforts to sensitive areas.

3. Vector Autoregression: Applications in the Forest Sector

Studies using short-term forecasting of forest products remain scarce (Hetemäki et al., 2004; Toppinen & Kuuluvainen, 2010), and mostly are directed at large geographic or administrative areas. Several analysts have applied different time series models to examine varying aspects of the forest products sector. Hetemäki et al. (2004) analyzed the effect of import demand on

Finnish forecasts of lumber exports and Finland's demand for saw-logs. The authors concluded that compared to a simple autoregressive process, AR(1), adding the complexity of a VAR system does not significantly improve the forecast. Malaty et al. (2007) forecast stumpage prices for pine saw-logs in Finland found the VAR having the largest forecast error among the methods evaluated. In contrast, Hetemäki & Mikkola (2005) forecasts for paper imports in Germany showed the VAR with exogenous regressors (VARX) provides better results compared to other methods. Likewise, using multiple time series models to forecast stumpage prices for U.S. pine sawtimber, Mei, Clutter, & Harris (2010) found the VAR predicts with more precision. The methods evaluated by Mei et al. (2010) include an autoregressive moving average (ARMA) model, a vector error correction (VEC) model, and a state space representation.

Additional research using VAR to forecast forest sector activity includes the works by Jennings, Adamowicz, & Constantino (1991), and Alavalapati, Luckert, & Adamowicz (1996) on Canadian lumber and pulp markets, respectively. Alavalapati et al. (1996) examined the effect of shocks to the exchange rate on pulp domestic demand. The findings support the use of macroeconomic variables in the analysis of forest products prices and domestic demand. In effect, the authors reported that shocks to the exchange rate significantly affect Canada's pulp prices (Alavalapati et al., 1996). Similarly, the work by Jennings et al. (1991) provides evidence for the use of VAR to short-term forecast. In this work, the authors forecasted Canada's lumber industry with a VAR system incorporating and array of macroeconomic variables such as GNP, exchange rate, and housing starts.

Most research uses macroeconomic variables to help generate forecasts for timber products markets within large geographic or administrative areas. An exception is Buongiorno et al. (1988), who incorporates macroeconomic variables to observe effects on harvests within a county. The authors used housing starts, lumber prices, and information on cut saw timber volumes to forecast harvests by major land ownership type (private and public). They used a linear feedback methodology similar to a VAR. According to their results, harvests in public lands show a stronger response to a shock in housing starts than private lands (Buongiorno et al., 1988). The authors cite forest conditions as a likely reason for the lack of significance of housing starts on private land harvests. In their study area (Pacific Northwest), most timber harvest originated from mature stands. On these slow-growing stands, the cost of delaying harvest likely exceeds the benefit of higher expected returns from increases in housing starts (Buongiorno et al., 1988). Jennings et al. (1991), on the other hand, found shocks on housing starts strongly influencing the lumber sector, with the effects lasting over a year before reverting to pre-shock levels.

The research developed in this chapter shares some similarities with Buongiorno et al. (1988), with some notable differences including the following:

First, the scope of the current study is larger. Buongiorno et al. (1988) examine harvest on 3 areas in the state of Oregon (one county, and two areas with two aggregated counties each). In contrast, we examined roundwood production (timber harvest) for individual counties in the state of Florida. The study area corresponds to Florida's Northwest FIA survey unit which includes 16 counties.

These two studies focus on very distinct regions of the country. Buongiorno et al. (1988) examined counties in the Pacific Northwest (PNW), while the current research focuses on an area within the Southeast region (SE). Differences between these two regions include forest characteristics and landownership. In terms of forest characteristics, the PNW timberlands contain older trees in larger size classes. Estimates for 2007 indicate that 24 percent of the PNW timberland contains trees in age classes of more than 100 years, compared to two percent of the SE timberland. Further, 57 percent of the SE timberland included trees in age classes of less than 40 years. Describing the timberland in terms of tree-size distribution, large trees (sawtimber size) make up the majority of the PNW timberland (68 percent) compared to less than half (47 percent) in the SE region. By contrast, poletimber and seedlings combined account for only 30 percent of the PNW timberland, compared with 52 percent in the SE. An even sharper contrast exists between these two regions timberland ownership distribution. While federal, state and local governments control the majority of the PNW timberland area, the opposite trend occurs in the SE, where private landownership dominates (Smith et al., 2009).

The Buongiorno et al. (1988) forecasts focus on sawtimber volumes (the most relevant product in their study area), while the following research explores pulpwood volumes. The SE region is the nation's leading pulpwood producer (Smith et al., 2009), which justifies the development of a model for this product.

Lastly, the methodology developed in this chapter diverges from Buongiorno et al. (1988) on various aspects regarding specification and testing. First, we test both the stationarity and cointegration assumptions. Second, we evaluate the series for structural breaks, which if present, can distort the stationarity tests (Perron, 1989). Lastly, we assess forecast precision for a set of VAR specifications, comparing the errors with that of a naïve one-step-forward forecast, using the last three years of data and the mean absolute scale error criteria.

4. The VAR Models

A. Structural and Reduced-Form VAR

The VAR allows the analysis of interrelated time series by making use of lagged observations. In a VAR, variables are treated symmetrically, affecting each other's past and current outcomes. For instance, considering two variables, y_t is affected from past and current realizations of z_t and vice versa (Enders, 2003). The structural VAR for these two variables, assuming a one-period lag, is expressed as

$$\begin{aligned} y_t &= b_{10} - b_{12} z_t + \delta_{11} y_{t-1} + \delta_{12} z_{t-1} + \varepsilon_{yt} \\ z_t &= b_{20} - b_{21} y_t + \delta_{21} y_{t-1} + \delta_{22} z_{t-1} + \varepsilon_{zt}, \end{aligned}$$

where y_t and z_t are assumed stationary. Additionally, ε_{yt} and ε_{zt} are assumed uncorrelated, white noise disturbances with respective standard deviations σ_y and σ_z. In the above system, the feedback is incorporated through the effects of y_t on z_t and z_t on y_t. Because of this feedback, the structural VAR cannot be estimated directly. Instead, one estimates the standard VAR.

Following Enders (2003), left-multiplying the structural VAR, in matrix form, by $\begin{pmatrix} 1 & b_{12} \\ b_{21} & 1 \end{pmatrix}^{-1}$

results in the standard, or reduced form, VAR,

$$y_t = \underbrace{(b_{10} - b_{12}b_{20})}_{a_{10}} + \underbrace{(\delta_{11} - b_{12}\delta_{21})}_{a_{11}} y_{t-1} + \underbrace{(\delta_{12} - b_{12}\delta_{22})}_{a_{12}} z_{t-1} + \underbrace{(\varepsilon_{yt} - b_{12}\varepsilon_{zt})}_{e_{1t}}$$
$$z_t = \underbrace{(b_{20} - b_{21}b_{10})}_{a_{20}} + \underbrace{(\delta_{21} - b_{21}\delta_{11})}_{a_{21}} y_{t-1} + \underbrace{(\delta_{22} - b_{21}\delta_{12})}_{a_{22}} z_{t-1} + \underbrace{(\varepsilon_{zt} - b_{21}\varepsilon_{yt})}_{e_{2t}}.$$

Or, expressed in its common condensed form,

$$y_t = a_{10} + a_{11}y_{t-1} + a_{12}z_{t-1} + e_{1t}$$
$$z_t = a_{20} + a_{21}y_{t-1} + a_{22}z_{t-1} + e_{2t}.$$

The standard VAR can be estimated consistently using equation-by-equation Ordinary Least Squares (OLS) (Enders, 2003; Hamilton, 1994). Nonetheless, the structural VAR remains under-identified, because in the standard form one solves for fewer parameters. In the case of two variables, for example, solving the standard VAR provides nine parameters, but the structural VAR includes ten unknowns. Therefore, recovering the parameters for the structural VAR requires additional identifying restrictions. For two variables, solving the structural VAR requires one additional restriction. For the case of *n* variables, identification requires $(n^2-n)/2$ restrictions. A commonly adopted identification assumption is that y_t possess no contemporaneous effect on z_t, or in other words, $b_{21}=0$. Under this assumption, the structural two-variable VAR system reduces to

$$y_t = b_{10} - b_{12}z_t + \delta_{11}y_{t-1} + \delta_{12}z_{t-1} + \varepsilon_{yt}$$
$$z_t = b_{20} \qquad + \delta_{21}y_{t-1} + \delta_{22}z_{t-1} + \varepsilon_{zt}.$$

B. Panel VAR (PVAR)

A panel specification provides an augmented sample size. To allow for county heterogeneity we can incorporate a county fixed effect as well as a time fixed effect to represent exogenous shocks in the system that would affect all counties similarly. Following Holtz-Eakin, Newey, & Rosen (1988) notation we can express the PVAR as

$$y_{it} = \alpha_{0t} + \sum_{l=1}^{L} \alpha_{lt} y_{it-l} + \sum_{l=1}^{L} \delta_{lt} z_{it-l} + \gamma f_i + \varphi d_t + e_{it},$$

where f_i represents the unobserved individual effect of county *i*, d_t is the unobserved time effect. α and δ are coefficients to be estimated, and y and z the system variables. The system includes lags *l*=1, …, *L*; cross-sectional units *i*=1, …, *N*; and time periods *t*=1,…, *T*.

C. Factor Analysis VAR (FAVAR)

VAR models are usually specified using only a few endogenous variables. Increasing the number of equations can consume degrees of freedom quite rapidly, as each new equation involves a new set of parameters to be estimated. Adding one equation to a two-equation three-lag system, for example, would increase the number of parameters to be estimated by 15. This can be a problem, especially when working with a short time series, as in the case of the present study. But using only a few variables to represent the dynamics of the variable of interest can result in a poor fit, with the consequent low ability to predict future values of the series. To specify a model that incorporates more information without the need for a large number of equations, Bernanke, Boivin, & Eliasz (2005) propose using factor analysis. In this manner, incorporating factor variables estimated from a larger set of variables as additional endogenous variables in the VAR system.

Let X_t represent a vector or observable macroeconomic variables which contains the vector of endogenous variables modeled, Z_t. Following Stock and Watson (2002), we can further assume that the information from the set can be summarized by a vector of unobservable factors F_t such that

$$X_t = \Gamma F_t + \Lambda Z_t + \eta_t$$

where the information set is represented by the observed macroeconomic variables and unobserved factors, plus a random unobserved component η_t. Γ is a matrix of factor loadings. The FAVAR is expressed as,

$$\begin{bmatrix} F_t \\ Z_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Z_{t-1} \end{bmatrix} + \varepsilon_t$$

where $\Phi(L)$ represents a finite lag polynomial of order d; F_t is a vector of unobserved factors; Z_t is a vector of observable economic variables; and ε_t denotes the associated error term assumed to have mean zero.

The approach requires estimating the unobserved factors in F_t. Therefore the FAVAR estimation proceeds in two steps. In the first step we use all the variables in X_t to estimate a set of principal components. Because the components include information from Z_t, a further adjustment was required before estimating the FAVAR. This process involved determining a subset of variables in X_t considered slow moving. Slow moving variables are those believed not to be affected contemporaneously by a shock affecting the endogenous variables in Z_t (Bernanke et al., 2005).

5. Empirical Application

We use the VAR method to forecast the volume of pulpwood production for counties in Florida's Northwest FIA survey unit (Figure III.1). The 16 counties comprise 36 percent of the

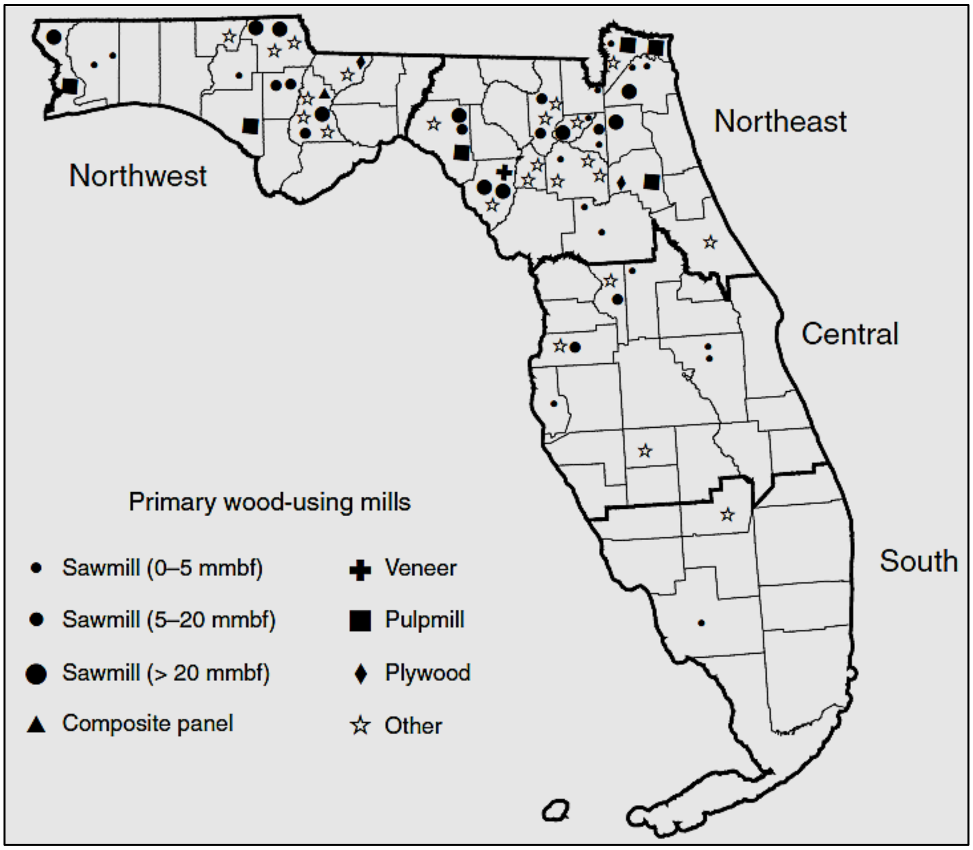


Figure III.1 Distribution of primary wood-using mills in Florida.
Source: Johnson et al. (2009).

state's timberland resources (Brown, 2007), close to 30 percent of the mill capacity (based on total number of mills), and 57 percent of all the roundwood produced by the state during 2007 (Johnson, Bentley, et al., 2009). Given the low representation of volume in hardwood species, only the softwood volumes were included. We modeled the systems with three endogenous variables including the volume of timber receipts from each respective county, the U.S. real GDP, and the PPI as a proxy for pulpwood prices. Additionally, we assessed the forecast performance of a four equations system, including the US-Canada exchange rate as an additional endogenous variable. We expect the US-Canada exchange rate (EXC) to capture the effect of wood pulp imports. Canada is the U.S. largest source of imported pulpwood (Daniels & Hyde, 1986) while US-Canada exchange rates have been found to affect Canada's pulp production levels (Alavalapati et al., 1996). However, with a small dataset, such as the one available for county wood pulp production, increasing the system with additional endogenous variables can potentially decrease the robustness of the estimation by increasing the number of parameters to be estimated. Alternatively, we can combine the counties and estimate the VAR as a panel, which affords us a larger sample size.

The TPO pulpwood series used include annual data collected from 1946 to 2009. Table III-1 displays information for variables and data sources. Additionally, Figures III.2 and III.3 provide a graphical display of the time series for each county, in levels. Estimations were carried out using Stata 12.0 statistical software (StataCorp, 2011).

A. Specification Issues

A significant consideration in the VAR specification involves the lag-length selection. In practice, the true number of lags is not known, and classical hypothesis testing is problematic

Table III-1 Variables description, summary statistics, units of measure, and data sources, pulpwood series.

Variable	Descrition	Units	Mean	Std. Dev.	Source
12005	Pulpmill volume, Bay county	standard cords	79,458	58,719	U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis, Timber Products Output program
12013	Pulpmill volume, Calhoun county	standard cords	81,459	44,723	
12033	Pulpmill volume, Escambia county	standard cords	56,084	17,091	
12037	Pulpmill volume, Franklin county	standard cords	37,735	36,793	
12039	Pulpmill volume, Gadsden county	standard cords	46,287	25,676	
12045	Pulpmill volume, Gulf county	standard cords	47,277	42,124	
12059	Pulpmill volume, Holmes county	standard cords	42,516	18,600	
12063	Pulpmill volume, Jackson county	standard cords	71,626	30,367	
12065	Pulpmill volume, Jefferson county	standard cords	41,340	20,482	
12073	Pulpmill volume, Leon county	standard cords	32,914	12,781	
12077	Pulpmill volume, Liberty county	standard cords	47,511	26,772	
12091	Pulpmill volume, Okaloosa county	standard cords	36,412	23,738	
12113	Pulpmill volume, Santa Rosa county	standard cords	81,493	32,380	
12129	Pulpmill volume, Wakulla county	standard cords	32,942	20,215	
12131	Pulpmill volume, Walton county	standard cords	63,323	32,289	
12133	Pulpmill volume, Washington county	standard cords	50,247	23,902	
rgdp	Real gross domestic product	Billions of dollars	7,219	3,552	U.S. Department of Commerce, Bureau of Economic Analysis
ppi	Producer price index for pulp, paper and allied products	index,1982=100	95	67	U.S. Department of Labor
xchg	US-Canada exchange rate	1US$=CAN			U.S. Treasury

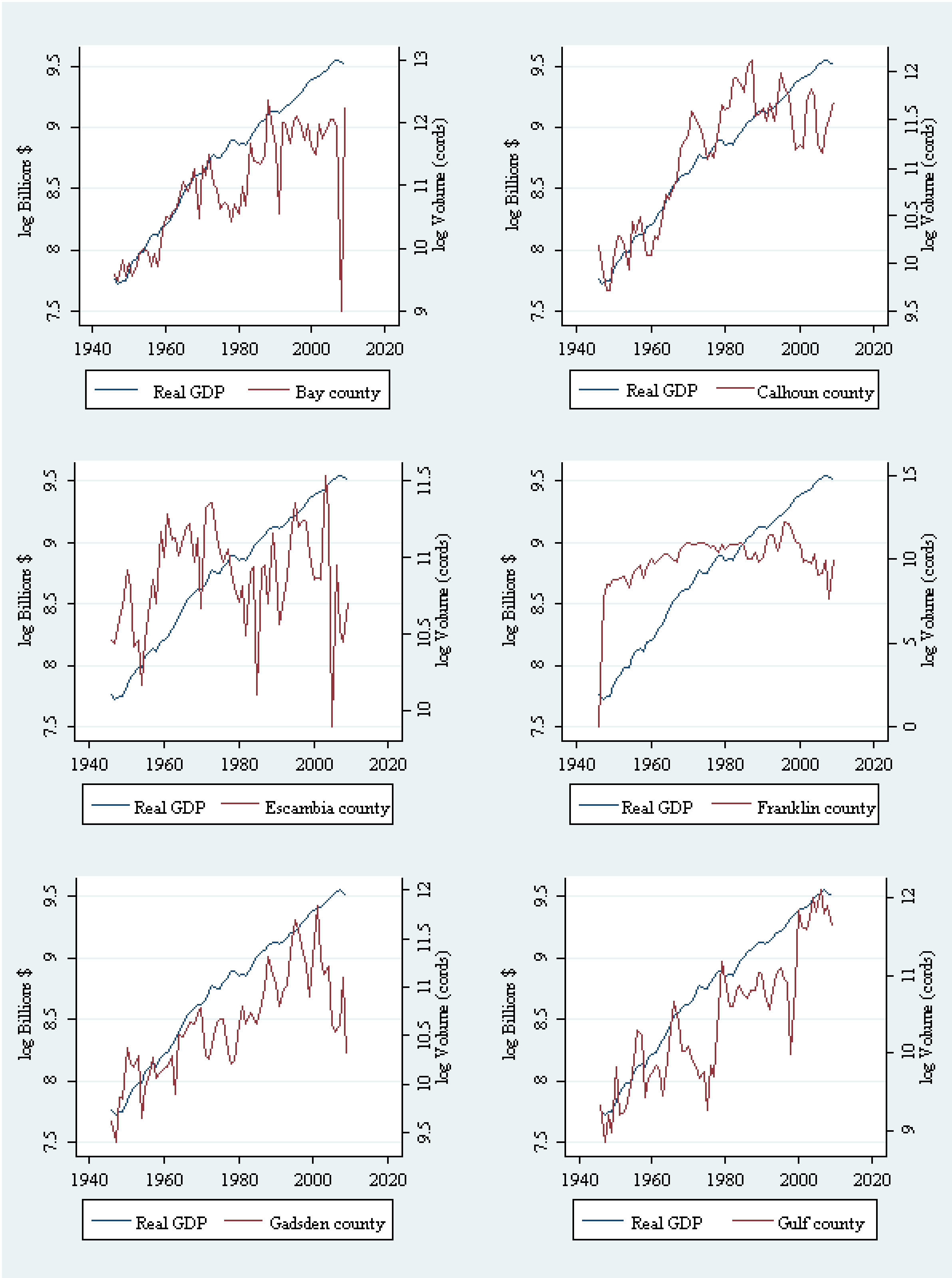


Figure III.2 Time series, GDP and pulpwood volume by county.

Figure III.2 Continued

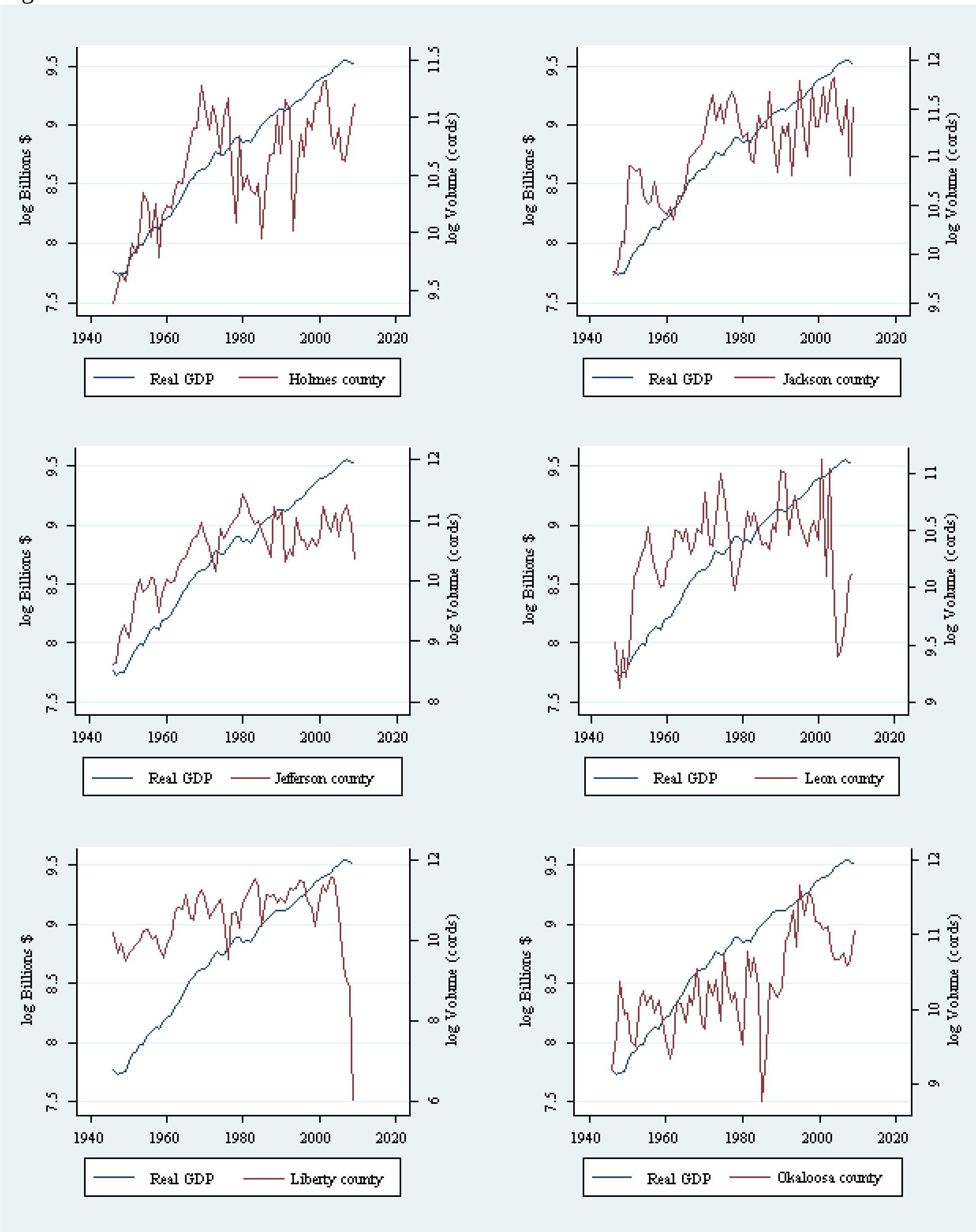
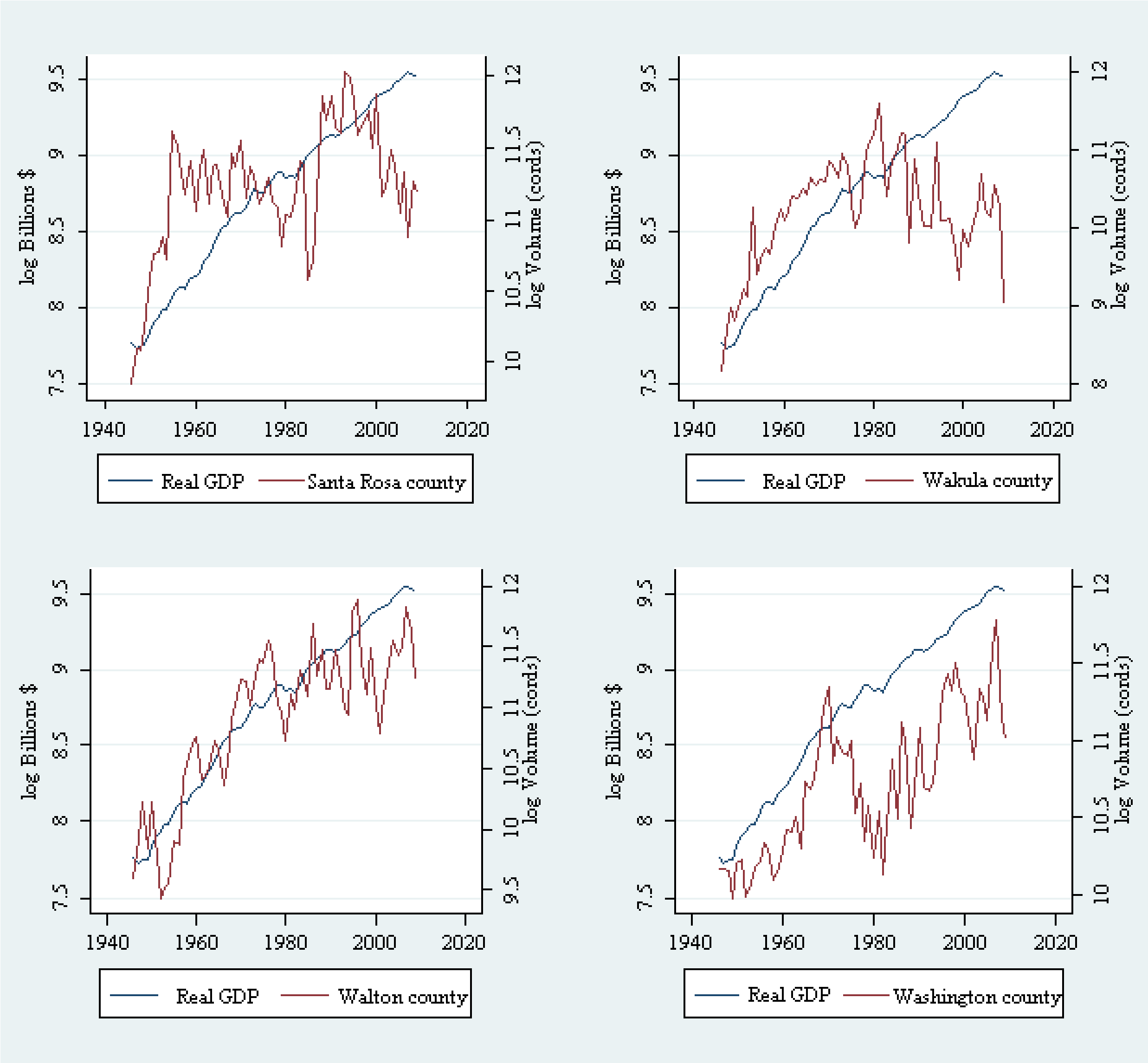


Figure III.2 Continued



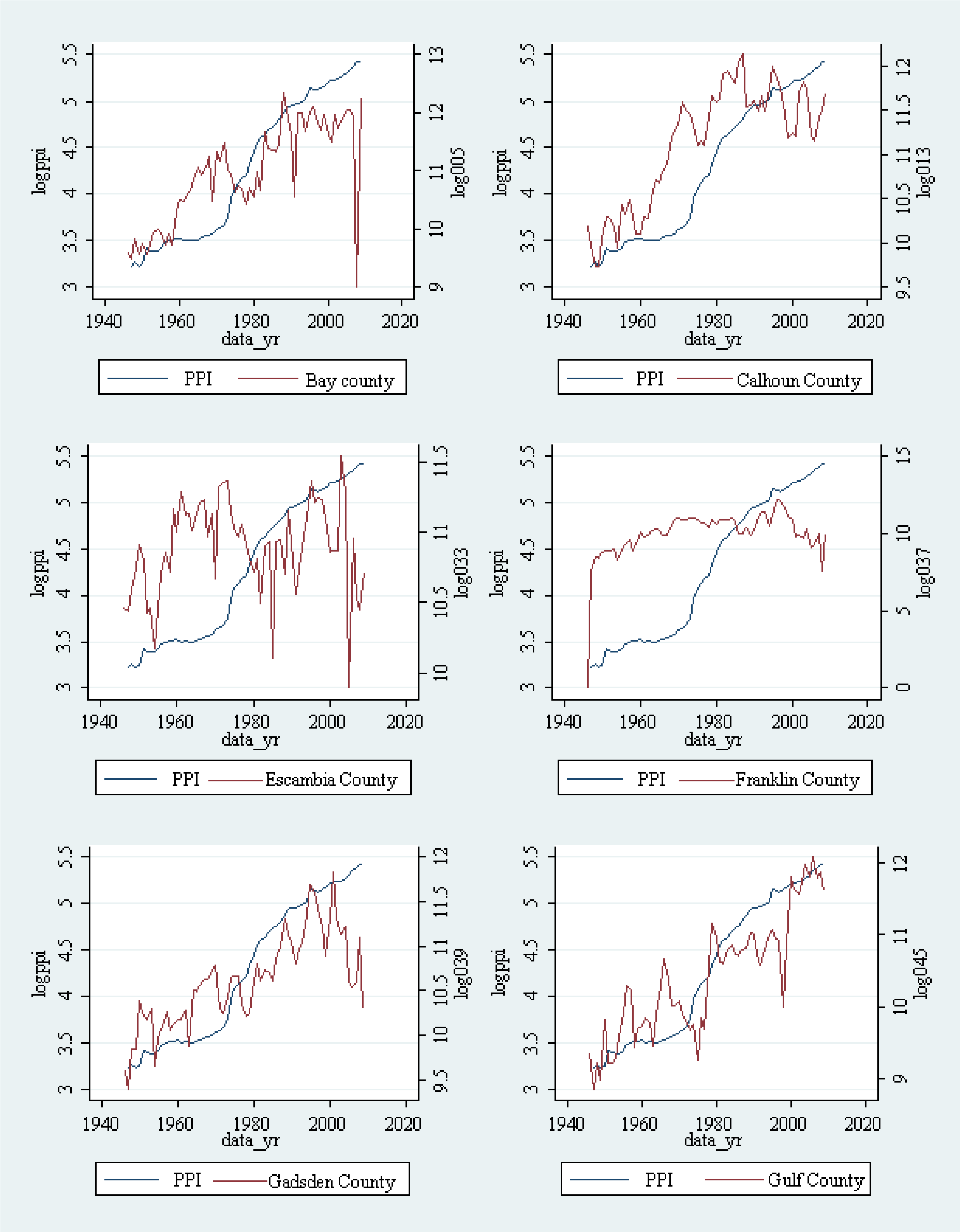


Figure III.3 Time series, PPI and county pulpwood series.

Figure III.3 Continued

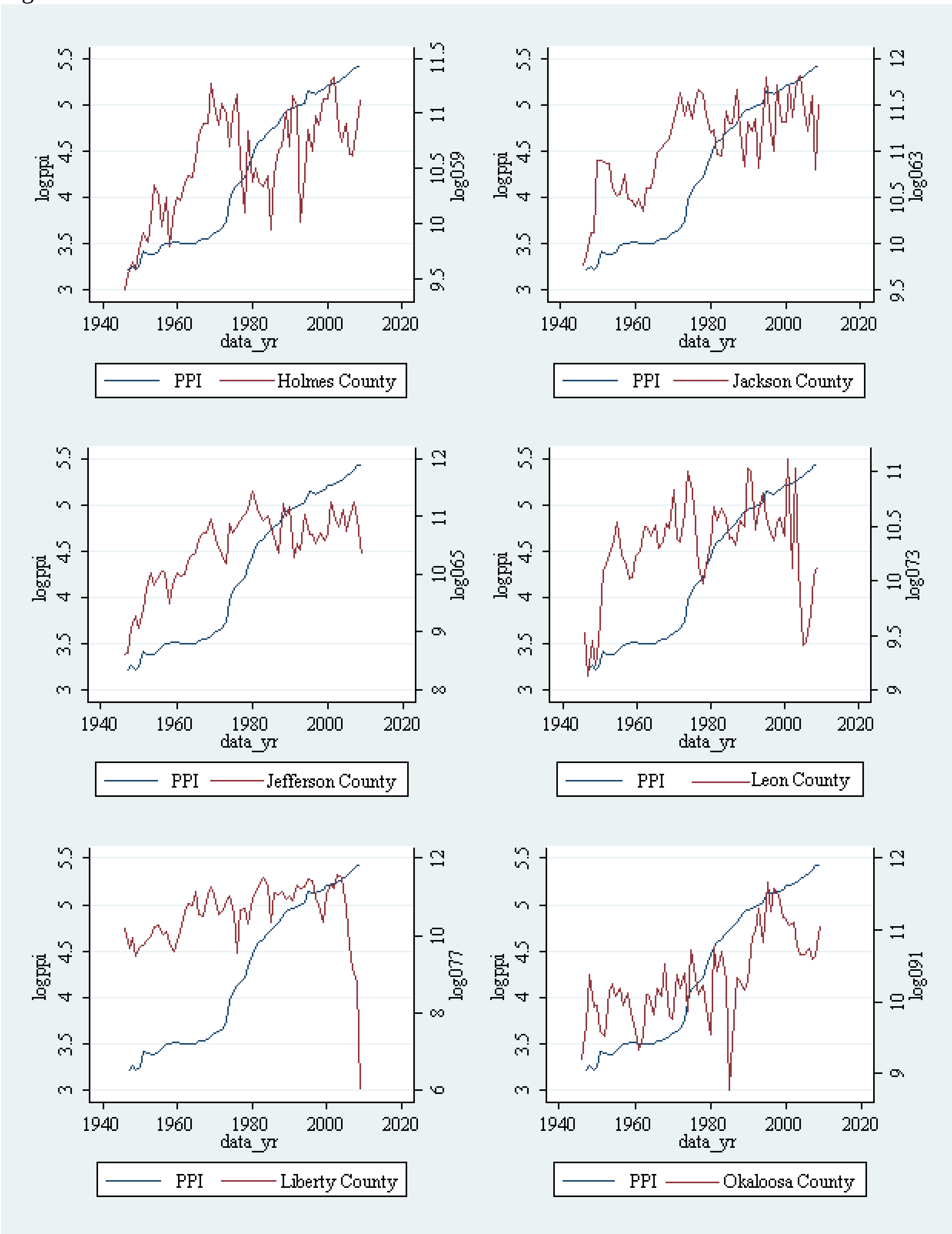
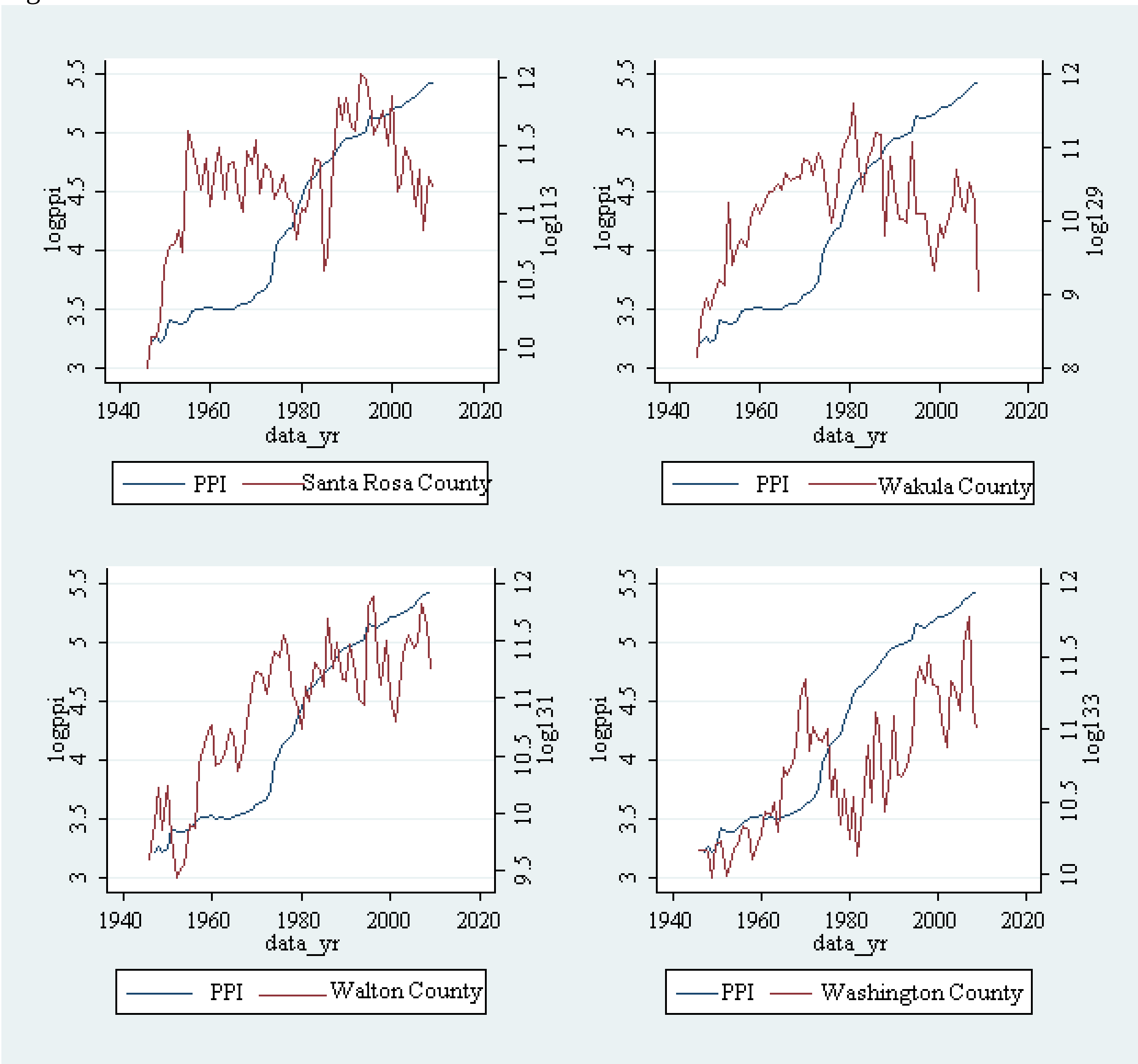


Figure III.3 Continued



given that the sample size decreases as the number of lags specified increases. Too many lags will reduce model efficiency, as lags can rapidly use degrees of freedom (Enders, 2003). Not enough lags to capture the interaction between the variables will result in omitted variables bias (Enders, 2003). Two commonly used methods for lag selection include the Akaike information criterion (AIC) and the Schwarz Bayesian information criterion (SIC).

$$AIC = \ln|\Sigma| + 2\frac{N}{T}$$
$$SIC = \ln|\Sigma| + \frac{N}{T}\ln(T),$$

where

T = Number of observations.

$|\Sigma|$= Determinant of the variance-covariance matrix of residuals.

N= Number of parameters in the system;

N= $n^2p + p$ (where n is the number equations, and p the number of lags).

The SIC formulation includes a stronger penalty for large samples (ln (T) >2 for T>=8). Therefore the SIC will select smaller models (less lags). For the empirical estimation we selected the lags based on the AIC method, following Enders (2003) recommendation when dealing with a small sample. When selecting the number of lags, the common practice is to preserve symmetry by using the same lag number in all equations. This symmetry allows the use of OLS to consistently estimate the parameters. Therefore, the same lags were used on each system.

Before selecting the number of lags, however, one needs to test for the presence of unit roots, as a unit root renders the process non-stationary. Two tests commonly used to assess presence of a unit root (non-stationary series) include the augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests. An issue with the ADF and PP tests is their low power when dealing with a series with persistent stationary process, which results in higher acceptance of the null. Presence of multiple deterministic trends also affects the power of the ADF and PP tests. Elliott, Rothenberg, & Stock (1996) proposed a modified Dickey-Fuller test (DFGLS) which is more robust to deterministic trends and to persistent stationary processes, as well. The DFGLS transforms the time series using GLS (generalized least squares) prior to running the ADF test. The DFGLS also proved robust to small-sample size (Elliott et al., 1996). Like the ADF test, the DFGLS uses lags to deal with autocorrelation. The number of lags used for the test, therefore influences the results. Not enough lags results in remaining correlation to bias the results. Too many lags affect the power of tests. Ng & Perron (2001) proposed a modified AIC criterion (MAIC) tests with improved performance over the AIC and BIC for non-stationary series.

For the current analysis, we evaluated the unit root tests using the number of lags suggested by the MAIC criterion. The tests were performed for the variables in levels and first differences. For level variables that show trending, we specified the ADF and PP tests with a trend. The DFGLS test includes a trend by default. Tests for the variables in differences were carried out without the trend.

When dealing with non-stationary series, the common approach to make the process stationary consists of using the variables' first differences. Some authors, however, argue that information is lost when using the variables on differences instead of their levels (Alavalapati et al., 1996; Jennings et al., 1991). Nonetheless, the use of differences is common in the literature (Hetemäki

& Mikkola, 2005; Malaty et al., 2007). Differencing non-stationary variables, however, is only possible when the variables are not cointegrated.

Cointegration between two variables indicates the existence of a long run relationship (cite). Two random variables are cointegrated if they are integrated of the same order *d*, but their linear combination is integrated of order *d-1*. The most typical case of cointegration involves two series with integration of order one, or I(1) series, that have a linear combination integrated of order zero, or I(0). Cointegration of I(1) variables is tested analyzing the residuals from the regression of the two variables. The test examines the residuals for a unit root. Finding a unit root on the residuals confirms the variables are not cointegrated (Enders, 2003). Cointegrated variables would require the specification of a vector error model (VEC), instead of the standard VAR. Before running cointegration tests, however, one needs to check the series for structural breaks. An additional assumption when using a time series is that the underlying process is the same across observations. However, many series include breaks resulting from external shocks, for example, from policy changes. Perron (1989) studied the relationship between breaks and unit roots and found that structural breaks significantly affect the results from unit root tests. In effect, series believed having a unit root proved stationary after controlling for a pre-determined shock (Perron, 1989). Structural breaks can also affect cointegration tests. Hetemäki et al. (2004) suggest using a VAR model in differences to help the performance of models that have irregular behavior or structural breaks. However, first differences only work if the variables are not cointegrated. Consequently, we tested for cointegration using the test proposed by Gregory and Hansen, which takes into account structural breaks at unknown dates (Gregory & Hansen, 1996). Additionally, we applied the Johansen cointegration test using a restriction on the trend and the intercept. The latter test is sensitive to the number of lags specified. Lags were selected using the AIC and FPE criteria on each system in levels. Lastly, we used the Zivot and Andrews (ZA) test to investigate presence of series break under different scenarios, a trend break, a break in constant and a combination of both. For the VAR specification, we controlled for the breaks determined by the ZA test using dummy variables as exogenous regressors. These break indicator variables take the value of one starting on the date of the break forward, and zero before the break.

In the Panel VAR specification we also need to consider the endogeneity of the fixed effects which are correlated with the regressors through the lags of the dependent variable. Love and Zicchino (2006) recommend using forward mean differencing to transform the variables and remove the individual fixed effects. This transformation allows the use of the lagged regressors as instruments (Love & Zicchino, 2006). The time fixed effects, on the other hand, can be differenced out without transformations.

B. The Empirical Models

In the case of the simple VAR and FAVAR specifications, guided by the results obtained from the unit root and structural break tests, we specified the equations using the variables in first differences. Additionally, we used log transformed variables to facilitate interpretation (log differences can be interpreted as percentage of change), and reduce heteroskedasticity. The pulpwood series includes 63 observations, leaving 62 observations after taking first-differences. We reserved the last three observations for the forecast evaluation, resulting in 59 observations available for estimation. The actual number of observation to estimate each system depended in the number of lags needed. The number of lags for each system was established using the AIC criteria for a VAR with exogenous variables (break indicators). For each county we estimated a VAR model with three equations and one FAVAR model with the added equations for two identified factors. Additionally, we combined the counties into a panel set and estimated the model with the three endogenous variables (PVAR1), as well as, with the US-Canada exchange rate as a fourth endogenous variable (PVAR2). The following standard VAR systems were estimated,

<u>*VAR – Three endogenous variables*</u>

$$PU_t = \delta_{10} + \sum_{l=1}^{p} \delta_{11}^{l} PU_{t-l} + \sum_{l=1}^{p} \delta_{12}^{l} GDP_{t-l} + \sum_{l=1}^{p} \delta_{13}^{l} PPI_{t-l} + \eta_{1t}$$

$$GDP_t = \delta_{20} + \sum_{l=1}^{p} \delta_{21}^{l} PU_{t-l} + \sum_{l=1}^{p} \delta_{22}^{l} GDP_{t-l} + \sum_{l=1}^{p} \delta_{23}^{l} PPI_{t-l} + \eta_{2t}$$

$$PPI_t = \delta_{30} + \sum_{l=1}^{p} \delta_{31}^{l} PU_{t-l} + \sum_{l=1}^{p} \delta_{32}^{l} GDP_{t-l} + \sum_{l=1}^{p} \delta_{33}^{l} PPI_{t-l} + \eta_{3t}$$

<u>*FAVAR – Three endogenous plus two factors variables*</u>

$$PU_t = \gamma_{10} + \sum_{l=1}^{p} \gamma_{11}^{l} PU_{t-l} + \sum_{l=1}^{p} \gamma_{12}^{l} GDP_{t-l} + \sum_{l=1}^{p} \gamma_{13}^{l} PPI_{t-l} + \sum_{l=1}^{p} \gamma_{14}^{l} F_{t-l}^{1} + \sum_{l=1}^{p} \gamma_{15}^{l} F_{t-l}^{2} + \upsilon_{1t}$$

$$GDP_t = \gamma_{20} + \sum_{l=1}^{p} \gamma_{21}^{l} PU_{t-l} + \sum_{l=1}^{p} \gamma_{22}^{l} GDP_{t-l} + \sum_{l=1}^{p} \gamma_{23}^{l} PPI_{t-l} + \sum_{l=1}^{p} \gamma_{24}^{l} F_{t-l}^{1} + \sum_{l=1}^{p} \gamma_{25}^{l} F_{t-l}^{2} + \upsilon_{2t}$$

$$PPI_t = \gamma_{30} + \sum_{l=1}^{p} \gamma_{31}^{l} PU_{t-l} + \sum_{l=1}^{p} \gamma_{32}^{l} GDP_{t-l} + \sum_{l=1}^{p} \gamma_{33}^{l} PPI_{t-l} + \sum_{l=1}^{p} \gamma_{34}^{l} F_{t-l}^{1} + \sum_{l=1}^{p} \gamma_{35}^{l} F_{t-l}^{2} + \upsilon_{3t}$$

$$F_t^1 = \gamma_{40} + \sum_{l=1}^{p} \gamma_{41}^{l} PU_{t-l} + \sum_{l=1}^{p} \gamma_{42}^{l} GDP_{t-l} + \sum_{l=1}^{p} \gamma_{43}^{l} PPI_{t-l} + \sum_{l=1}^{p} \gamma_{44}^{l} F_{t-l}^{1} + \sum_{l=1}^{p} \gamma_{45}^{l} F_{t-l}^{2} + \upsilon_{4t}$$

$$F_t^2 = \gamma_{50} + \sum_{l=1}^{p} \gamma_{51}^{l} PU_{t-l} + \sum_{l=1}^{p} \gamma_{52}^{l} GDP_{t-l} + \sum_{l=1}^{p} \gamma_{53}^{l} PPI_{t-l} + \sum_{l=1}^{p} \gamma_{54}^{l} F_{t-l}^{1} + \sum_{l=1}^{p} \gamma_{55}^{l} F_{t-l}^{2} + \upsilon_{5t}$$

PVAR1- Three endogenous variables

$$Z_{it} = \Gamma_0 + \sum_{l=1}^{p} \Gamma_l Z_{it-l} + \gamma f_i + \varphi d_t + \varepsilon_{it} ,$$

$$Z = \{PU, GDP, PPI\} .$$

PVAR2- Four endogenous variables

$$Z_{it} = \Gamma_0 + \sum_{l=1}^{p} \Gamma_l Z_{it-l} + \gamma f_i + \varphi d_t + \varepsilon_{it} ,$$

$$Z = \{PU, GDP, PPI, EXC\} .$$

Where,

l = Lag number (*l* =1,…, p),

PU = County volume of pulpwood receipts from pulp mills,

GDP = U.S. Real gross domestic product (base 2007),

PPI = Producer price index for pulp, paper and allied products (100=1982),

EXC = US-Canada exchange rate,

Z = Vector of endogenous variables,

F = Factor variables

ε_{it} , υ_{it} , and η_{it}= error terms, assumed *i.i.d.~(0,D).*

After estimating the standard VAR we evaluated whether the macroeconomic variables selected (z_t) influenced the path of a county's wood volume production, y_t via a Granger causality test. If for example, past and current values of z_t do not predict current values of y_t, then z_t lacks forecasting power for y_t. Therefore, adding z_t to the system will provide no further help in predicting y_t. Formally, in a system with *p* lags, evaluating if z_t Granger-causes y_t means testing the joint restriction $a_{12}(1) = a_{12}(2) = ... = a_{12}(p) = 0$. Rejecting the null gives evidence of z_t Granger causing y_t.

For the FAVAR estimation we needed to identify slow moving variables to isolate the factor components from effects in the endogenous variables. We assumed slow movement for variables related to personal consumption and interest rates with the belief that those indicators affect or are affected by the endogenous variables only with a lag. Similarly, we assumed the set of fast moving variables included variables closer related to industrial production, such as manufacturing employment and industrial capacity. The list of variables used to estimate the factors is provided in the appendix. We used the estimated unobservable factors as additional endogenous variables in the VAR.

We evaluated the forecast precision between the different specifications, using the mean absolute percent error (MAPE). Additionally, we compared the forecasts from the VAR specifications with the forecast from a simple step-forward method. We compared the results from both methods using the mean absolute scaled error (MASE) measures. We also obtained the mean squared forecast error (MSFE) and the mean absolute forecast error (MAD) for each forecast approach. These measurement were estimated as follows,

$$MSFE = \frac{\sum_{T}^{T+h} (\hat{y}_{t+1} - y_{t+1})^2}{h}$$

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

$$MAD = \frac{1}{h} \times \sum_{T}^{T+h} \left| y_{t+1} - \hat{y}_{t+1} \right|$$

$$MASE = \frac{MAD_{VAR}}{MAD_{SF}}$$

Where

T = Start point for forecast

h = Number of forecast periods

y_{t+1} = Actual value at time t+1

$\hat{y}_{t+1}$ = Forecast value at time t+1

SF = Step-Forward forecast

6. Results and Discussion

A. VAR General Tests

Initial graphical analysis of the pulp, GDP, and PPI series revealed mixed results across counties. While overall the three series do not appear to move close together, production from a few counties mirrored the DGP series with some proximity. Specifically Calhoun, Gadsden and Walton counties (Figure III.2) followed GDP to some degree, although, these similarities decreased considerably for observations after the 1990s. Surprisingly, the PPI series did not appear to move closely with the pulp volume as often as the GDP series, as seen in Figure III.3.

Further evaluation of the series showed most counties having a unit root, although the tests yielded varied results. As seen in Table III-2, across all three tests, we reject the null hypothesis of a unit root for Gulf county only. In effect, Gulf was the only county where the DF-GLS test

Table III-2 Unit root tests pulpwood series, variables in levels.

Variable	Description	ADF-GLS Test-statistic	ADF-GLS Critical value 5%	ADF-GLS MAIC lags	ADF Test-statistic	ADF Critical value 5%	PP Test-statistic	PP Critical value 5%
log005	Bay county	-1.546	-3.020	4	-1.370	-3.491	-6.407**	-3.487
log013	Calhoun	-1.335	-3.020	4	-1.087	-3.491	-2.021	-3.487
log033	Escambia	-0.923	-2.181	2	-2.718	-2.921	-5.094**	-2.920
log037	Franklin	-0.094	-2.194	1	-3.458**	-2.920	-9.496**	-2.920
log039	Gadsden	-1.101	-2.980	5	-0.271	-3.492	-3.167	-3.487
log045	Gulf	-4.15**	-3.110	1	-4.086**	-3.488	-4.290**	-3.487
log059	Holmes	-1.695	-3.086	2	-2.320	-3.489	-3.646**	-3.487
log063	Jackson	-1.637	-3.086	2	-2.686	-3.489	-4.348**	-3.487
log065	Jefferson	-0.952	-3.056	3	-2.084	-3.490	-2.731	-3.487
log073	Leon	-1.046	-2.935	6	-1.711	-3.493	-3.222	-3.487
log077	Liberty	-0.393	-2.194	1	0.195	-2.920	0.320	-2.920
log091	Okaloosa	-2.335	-3.020	4	-2.282	-3.491	-4.657**	-3.487
log113	Santa Rosa	-1.282	-3.056	3	-2.900	-3.490	-3.634**	-3.487
log129	Wakulla	-1.024	-3.086	2	-2.001	-3.489	-2.854	-3.487
log131	Walton	-1.351	-2.935	6	-1.882	-3.493	-3.372	-3.487
log133	Washington	-2.436	-3.086	2	-2.397	-3.489	-3.990**	-3.487
loggdp	Real GDP	-1.480	-3.110	1	-1.484	-3.488	-0.932	-3.487
logppi	PPI	-1.443	-3.114	1	-1.703	-3.489	-1.449	-3.488

Notes: **= Null of a unit root rejected for a 5% critical value.

rejected the null of a unit root at the five percent confidence level. In other words, of the 16 county series examined only one can be considered stationary in levels. Across the three tests, the PP test rejected the null with a much higher frequency, estimating almost 50 percent of the series as stationary. Tests results for the series in differences, found in Table III-3, show PP tests rejected the null of a unit root in all instances, while the ADF and DF-GLS tests rejected the null in only a handful of cases. The pulpwood series for Escambia, Jefferson and Washington counties revealed a stationary series for the variable in differences across all three tests. A rather high number of lags were needed for the variables in differences, compared to the optimal lags when using the variables in levels. Longer lags point to persistent processes that take longer to revert to the mean, although the long lags (e.g. Wakulla or Walton counties) did not correspond to stationary series.

Table III-4 provides a summary of results from the cointegration tests. The test without structural breaks (Johansen test) showed several series where we rejected the null of no cointegration with both the trend constant and trend unrestricted options. Applying the Gregory-Hansen test, however, revealed that when controlling for structural breaks in trend and slope, only Bay county continued to show signs of cointegration. Consequently, we can use the variables in differences but needed also to control for structural breaks. The Zivot and Andrews tests for structural breaks provided further evidence for the existence of breaks in all series (Table III-5). Taking these breaks into account caused a number of the series to become stationary in levels. For example, Washington county series was stationary in levels after controlling for a break in trend and intercept occurring in 1976. The series however continued to signal a unit root after controlling for a break in trend in 1968. In contrast, the null of a unit root

Table III-3 Unit root tests pulpwood series, variables in first-differences.

Variable	Description	ADF-GLS Test-statistic	ADF-GLS Critical value 5%	ADF-GLS MAIC lags	ADF Test-statistic	ADF Critical value 5%	PP Test-statistic	PP Critical value 5%
dlog005	Bay county	-0.466	-2.023	10	-1.816	-2.928	-15.772**	-2.92
dlog013	Calhoun	-0.961	-2.084	7	-2.646	-2.926	-7.512**	-2.92
dlog033	Escambia	-5.742**	-2.184	2	-5.700**	-2.922	-13.476**	-2.92
dlog037	Franklin	0.038	-2.106	6	-3.248**	-2.925	-18.894**	-2.92
dlog039	Gadsden	-0.951	-2.061	8	-0.470	-2.927	-9.503**	-2.92
dlog045	Gulf	-0.668	-2.023	10	-3.370**	-2.928	-11.693**	-2.92
dlog059	Holmes	-1.185	-2.041	9	-2.490	-2.928	-12.556**	-2.92
dlog063	Jackson	-0.712	-2.023	10	-2.193	-2.928	-12.786**	-2.92
dlog065	Jefferson	-6.119**	-2.198	1	-6.182**	-2.921	-9.553**	-2.92
dlog073	Leon	-1.364	-2.041	9	-2.506	-2.928	-12.310**	-2.92
dlog077	Liberty	-1.081	-2.168	3	-0.733	-2.923	-5.800**	-2.92
dlog091	Okaloosa	-0.623	-2.061	8	-2.779	-2.927	-12.622**	-2.92
dlog113	Santa Rosa	-0.545	-2.084	7	-2.061	-2.926	-10.686**	-2.92
dlog129	Wakulla	-0.107	-2.023	10	-1.890	-2.928	-11.240**	-2.92
dlog131	Walton	-0.577	-2.023	10	-2.887	-2.928	-11.555**	-2.92
dlog133	Washington	-4.042**	-2.168	3	-4.104**	-2.923	-11.444**	-2.92
dloggdp	Real GDP	-1.212	-2.128	5	-2.505	-2.924	-6.558**	-2.92
dlogppi	PPI	-1.776	-2.152	4	-1.760	-2.924	-5.388**	-2.92

Notes: **= Null of a unit root rejected for 5% critical value.

Table III-4 Results from cointegration tests, pulpwood series.

			Johansen test maximum rank=0		Gregory -Hansen test	
Variable	County	AIC Lags	Test-statistic Trend Constant	Test-statistic Trend Unrestricted	Test-statistic break in trend & slope	Break date
log005	Bay	1	59.63*	63.86*	-82.06*	1978
log013	Calhoun	2	25.90	27.67	-39.52	1967
log033	Escambia	2	30.68*	26.00	-65.90	1994
log037	Franklin	2	24.42	20.46	-63.85	1998
log039	Gadsden	2	29.76*	26.86	-46.24	1993
log045	Gulf	2	30.66*	26.44	-44.52	1977
log059	Holmes	2	38.90*	34.01	-53.77	1996
log063	Jackson	2	49.17*	30.38	-63.01	1968
log065	Jefferson	2	26.23	26.19	-50.32	1977
log073	Leon	2	28.80	27.13	-43.11	1976
log077	Liberty	2	22.09	26.21	-51.95	1996
log091	Okaloosa	2	25.77	21.16	-52.64	1990
log113	Santa Rosa	2	27.75	24.00	-39.15	1987
log129	Wakulla	2	21.45	24.24	-53.97	1977
log131	Walton	2	34.60*	32.46	-48.43	1977
log133	Washington	2	29.01	26.15	-53.09	1975
5% Critical value			29.68	34.55	-68.43	

Notes: *= Null of no cointegration rejected at the 5% critical value.

Table III-5 T-statistics from Zivot & Andrews test, series break and unit root.

Variable	Description	Intercept	Break year	Trend	Break year	Trend & Intercept	Break year
				Levels			
log005	Bay county	-3.68	1960	-3.92	1999	-3.91	1995
log013	Calhoun	-3.62	1996	-4.31	1983	-4.42	1988
log033	Escambia	-3.55	1959	-3.21	1962	-3.49	1959
log037	Franklin	-4.98	1999	-5.09	1997	-5.17	1996
log039	Gadsden	-3.82	1999	-4.91	1999	-5.60	1994
log045	Gulf	-4.77	1999	-4.37	1998	-4.70	1968
log059	Holmes	-3.53	1977	-2.70	1967	-3.95	1977
log063	Jackson	-4.20	1966	-3.09	1973	-4.20	1966
log065	Jefferson	-4.43	1991	-4.85	1978	-5.19	1982
log073	Leon	-4.05	1995	-4.54	1956	-4.58	1990
log077	Liberty	0.80	1999	-1.37	1999	-1.67	1999
log091	Okaloosa	-6.05	1991	-4.84	1962	-6.45	1991
log113	Santa Rosa	-4.27	1999	-4.50	1956	-4.86	1987
log129	Wakulla	-3.45	1988	-3.46	1971	-3.85	1988
log131	Walton	-4.86	1957	-4.74	1974	-5.03	1957
log133	Washington	-5.72	1976	-4.24	1968	-5.81	1976
loggdp	Real GDP	-2.59	1962	-4.60	1969	-4.53	1965
logppi	PPI	-4.55	1974	-2.04	1996	-4.13	1974
				First Difference			
log005	Bay county	-7.22	1981	-7.01	1997	-7.28	1981
log013	Calhoun	-6.24	1988	-5.94	2000	-6.25	1988
log033	Escambia	-9.52	1986	-9.27	1996	-9.51	1986
log037	Franklin	-10.40	1998	-9.92	1993	-10.40	1999
log039	Gadsden	-6.55	1980	-6.53	1996	-6.64	1994
log045	Gulf	-7.12	1976	-6.77	1961	-7.29	2000
log059	Holmes	-9.38	1986	-8.89	1979	-9.30	1986
log063	Jackson	-8.95	1984	-9.22	1957	-9.66	1957
log065	Jefferson	-7.03	1994	-6.93	2000	-6.81	1959
log073	Leon	-10.78	1979	10.62	1958	-10.71	1979
log077	Liberty	-6.48	1977	-7.75	2000	-9.00	2000
log091	Okaloosa	-8.16	1987	-7.85	1993	-8.38	1987
log113	Santa Rosa	-7.49	1987	-7.08	1961	-7.62	1987
log129	Wakulla	-8.14	2000	-7.82	1973	-8.18	2000

Table III-5 Continued

log131	Walton	-7.21	1977	-7.24	1958	-7.52	1960
log133	Washington	-8.41	1971	-7.90	1997	-8.52	1971
loggdp	Real GDP	-6.44	1984	-6.10	1981	-6.40	1984
logppi	PPI	-6.95	1973	-6.21	1980	-7.22	1973
	1% critical value	-5.43		-4.93		-5.57	
	5% critical value	-4.80		-4.42		-5.08	

was rejected at the one percent level in all differentiated series when controlling for breaks in trends and intercept. A few break patterns were noticeable, for instance, no breaks were identified during the 1962 to 1970 period. A good number of intercept breaks were found in the 1980s and mid-late 1970s. In effect, intercept breaks occurred in seven series between 1984 and 1988 and five series between 1976 and 1979. Conversely, a few more breaks in trend were identified from 1956 to 1961 (breaks in six series), and during the 1996-2000 period (nine series).

Lag selection for the VAR equations followed, after identifying and controlling for the break dates. Table III-6 presents the results of three lag selection methods. We used the optimum lag number selected by the AIC criteria, which outperforms other methods when dealing with small samples (Enders, 2003). The AIC selected a maximum of three lags for the majority of the equations, the exceptions being Santa Rosa and Washington each with four lags, and Liberty and Walton with zero lags each. For these last two series, the equations were estimated using one lag instead of zero.

B. The Standard VAR Specification

Table III-7 presents results from the standard VAR model. Only a few coefficients in this model proved significant, corroborating the preliminary graphical examination of the series. The GDP and PPI movements did not represent the observed movements in the volumes of pulpwood procurement series for all the counties in the sample. Nonetheless, the methodology proved useful to help predict procurement volume in 30 percent of the counties in the Northwest unit. GDP and PPI explained the volume series individually in a similar percent of cases. Only the Gulf county volume equation held both GDP and PPI as significant predictors within a 95

Table III-6 Optimal number of lags by different selection criteria for the VAR specification.

		Selection Criteria		
County	Variable	AIC	FPE	SBIC
Bay	log005	3	3	1
Calhoun	log013	3	3	0
Escambia	log033	3	3	0
Franklin	log037	3	3	1
Gadsden	log039	3	3	0
Gulf	log045	3	3	0
Holmes	log059	3	3	0
Jackson	log063	3	3	0
Jefferson	log065	3	3	0
Leon	log073	3	0	0
Liberty	log077	0	0	0
Okaloosa	log091	3	3	0
Santa Rosa	log113	4	3	0
Wakulla	log129	3	3	0
Walton	log131	0	0	0
Washington	log133	4	4	0

Table III-7 Coefficients significance in county volume equations, VAR model.

	D_loggdp				D_logppi			
Equation	Lag 1	Lag 2	Lag 3	Lag 4	Lag 1	Lag 2	Lag 3	Lag 4
	---------- *Prob* > |*t*| ----------							
D_log005	0.831	0.839	0.345	-	0.493	0.867	0.584	-
D_log013	0.121	0.947	0.136	-	0.052*	0.694	0.042**	-
D_log033	0.330	0.372	0.315	-	0.457	0.619	0.864	-
D_log037	0.186	0.210	0.206	-	0.944	0.960	0.358	-
D_log039	0.941	0.493	0.824	-	0.704	0.650	0.012**	-
D_log045	0.041**	0.152	0.169	-	0.14	0.727	0.001***	-
D_log059	0.973	0.287	0.030**	-	0.592	0.623	0.718	-
D_log063	0.507	0.735	0.412	-	0.442	0.697	0.321	-
D_log065	0.023**	0.451	0.619	-	0.348	0.935	0.704	-
D_log073	0.959	0.700	0.356	-	0.717	0.137	0.851	-
D_log077	0.242	-	-	-	0.255	-	-	-
D_log091	0.171	0.586	0.061*	-	0.855	0.628	0.518	-
D_log113	0.253	0.784	0.939	0.367	0.443	0.270	0.654	0.199
D_log129	0.403	0.277	0.697	-	0.076*	0.399	0.245	-
D_log131	0.113	-	-	-	0.567	-	-	-
D_log133	0.753	0.629	0.876	0.072*	0.844	0.187	0.376	0.144

Notes: ***= significant at 1%; **= significant at 5%; *= significant at 10%.

percent confidence level. After fitting the VAR model, we employed the Granger causality tests to assess the ability of the macroeconomic variables to predict the county volumes. Table III-8 provides a summary of the causality test from variable A to B for each volume equation. The first two columns of Table III-8 show the causality of GDP and PPI on the volume equations. Only Gadsden, Gulf, Okaloosa, and Walton counties displayed a five percent statistical significance, supporting the assumption of either GDP or PPI Granger causing the mentioned counties' pulpwood volumes. Further, the granger tests failed to support the theory of PPI causing GDP, instead providing evidence of PPI granger causing GDP in more than half of the counties. Likewise, county pulp volume (PV) was found to granger cause PPI in the Santa Rosa equation with a high significance level, as seen in Table III-8 columns three and four. The conflicting results in the causal relationship for PPI tests make the findings for the causal relationship on PV doubtful, as well. Possible explanations include the test's low power given by loss of information caused by using the series in differences and by a small sample.

C. The FAVAR Specification

The FAVAR estimation included two estimated factors, which were statistically significant in at least one cross equation for each county. The first factor proved significant to the volume equation with more frequency. The Granger causality tests displayed a similar pattern as that observed in the VAR specification. Although the macroeconomic variables and the factor variables granger caused pulpwood volumes in a series of counties, the wood production of a significant number of counties was not explained by the system variables. This suggests the need for alternative specifications that can support a larger set of variables such as the panel VAR.

Table III-8 F-statistic from Granger causality tests between endogenous variables, VAR model.

County	GDP to PV	PPI to PV	GDP to PPI	PV to PPI	PPI to GDP	PV to GDP
Bay	0.625	0.490	3.277**	1.029	1.469	0.157
Calhoun	1.096	2.180	2.457*	1.328	2.092	0.086
Escambia	0.921	0.278	2.408*	1.321	1.726	0.243
Franklin	1.812	0.372	3.278**	0.220	1.551	1.582
Gadsden	0.499	3.120**	2.064	0.480	0.967	0.955
Gulf	2.501*	4.191**	2.337*	2.439*	1.138	0.120
Holmes	2.280*	0.226	2.559*	0.625	1.637	1.014
Jackson	0.727	0.384	2.283*	0.939	1.907	1.130
Jefferson	0.744	0.682	3.163**	0.476	1.572	1.151
Leon	0.515	1.037	4.112**	1.830	1.739	0.246
Liberty	0.056	1.421	3.347*	0.022	5.976**	0.339
Okaloosa	3.000**	0.082	3.316**	0.796	1.626	0.285
Santa Rosa	0.748	0.850	5.454***	4.426***	2.453**	1.416
Wakulla	0.471	1.235	2.318*	0.290	1.244	2.380*
Walton	4.224**	0.293	4.039**	0.839	4.806**	0.918
Washington	0.881	0.962	2.672**	0.886	2.162*	1.134

Notes: GDP= Real gross domestic product; PPI = Producer price index; PV= Pulpwood volume. ***= significant at 1%; **= signifcant at 5%; *= significant at 10%

D. Forecasts

A forecast period of three years was evaluated with results displayed in Table III-9 and Table II-10. Forecast results across the four models showed mixed patterns, without a clear leading methodology. The squared forecast errors varied from decimal numbers to a few counties exhibiting double digit errors (Table III-9). While some models performed better in certain counties, the same models failed to provide significant forecasts for other counties. None of the models provided a MAPE under 50 percent, indicating poor fit and, perhaps, the need for a higher system. Considering the total MAPE value for the three-year forecast, the FAVAR model seemed to perform slightly better than the simple VAR model. The reduced percent of error from the FAVAR, compared to the VAR, provides evidence to support the need of additional information to identify the system dynamics. However, the results shown by Holmes county also indicate the need for information to capture the dynamics at the county level to help explain the variation across counties in the area. In part, the low predictability of the FAVAR could be the result of a small sample. The FAVAR augmented the VAR by two equations, and some counties needed up to four lags for identification, leaving few degrees of freedom for the estimation. The Panel specification allowed for a larger sample, and for most counties proved to predict future values with less average error (lower MAPE values). The inclusion of the exchange rates to the panel specification (PVAR2), however, resulted only in a slight change in MAPE.

Comparing the forecast from the above models with the results from a simple step-forward forecast revealed some gains in prediction power (Table III-10). We assessed the improvement of the vector autoregressive approach over the simple step-forward forecast using the MASE values. Values above one reveal no gain in the use of the alternate model. In effect, the smaller

Table III-9 Mean squared forecast error (MSFE) and Mean Absolute percent error across models for a three-year period forecast.

FIPS	MSFE					MAPE				
	SF	VAR	FAVAR	PVAR 1	PVAR 2	SF	VAR	FAVAR	PVAR 1	PVAR 2
Bay	15.56	6.48	6.08	17.97	17.97	128.11	132.28	73.90	96.45	93.89
Calhoun	0.05	0.02	0.05	0.01	0.01	113.79	61.57	117.08	89.93	98.31
Escambia	0.82	0.31	0.09	0.10	0.10	314.76	423.15	183.68	89.26	88.02
Franklin	10.50	4.90	5.28	13.63	13.64	136.31	130.42	131.41	100.89	101.82
Gadsden	0.21	0.05	0.06	0.40	0.40	158.85	139.33	81.53	106.49	109.44
Gulf	0.62	0.36	0.26	0.09	0.09	244.84	105.41	75.45	75.56	72.81
Holmes	0.05	0.06	0.35	0.04	0.04	1,494.83	206.38	4,675.66	133.00	123.06
Jackson	1.32	0.44	0.39	0.84	0.84	170.55	78.30	85.27	97.57	99.36
Jefferson	0.11	0.16	0.17	0.17	0.17	99.73	142.24	139.70	104.07	105.01
Leon	0.04	0.61	0.10	0.02	0.02	139.36	433.00	218.96	101.84	136.30
Liberty	2.13	2.36	3.11	12.57	12.58	74.19	71.64	171.51	103.52	104.08
Okaloosa	0.09	0.08	0.32	0.12	0.12	216.36	109.06	381.18	96.82	95.66
Santa Rosa	0.48	0.14	0.06	0.09	0.09	315.17	94.14	140.13	90.94	90.18
Wakulla	0.56	0.60	0.74	0.61	0.62	155.11	93.38	103.66	102.17	102.66
Walton	0.13	0.08	0.10	0.22	0.22	137.27	93.91	93.95	102.32	102.65
Washington	0.33	0.15	0.14	0.18	0.18	215.65	139.41	133.20	81.39	91.96

Notes: SF=Step-Forward, PVAR1= Panel VAR with three endogenous variables, PVAR2= Panel VAR with four endogenous variables.

Table III-10 Mean absolute scaled error comparison between vector autoregression methods and step-forward forecast approach for a three-year period forecast.

	MAD					MASE			
FIPS	SF	VAR	FAVAR	PVAR1	PVAR2	VAR	FAVAR	PVAR1	PVAR2
Bay	3.05	2.14	2.02	3.48	3.48	0.70	0.66	1.14	1.14
Calhoun	0.19	0.12	0.21	0.10	0.10	0.64	1.10	0.51	0.55
Escambia	0.72	0.46	0.28	0.30	0.30	0.64	0.39	0.42	0.41
Franklin	2.77	2.13	2.19	3.12	3.12	0.77	0.79	1.12	1.13
Gadsden	0.62	0.52	0.42	0.57	0.57	0.84	0.67	0.91	0.92
Gulf	0.45	0.22	0.21	0.25	0.25	0.48	0.46	0.57	0.55
Holmes	0.20	0.20	0.52	0.18	0.18	1.00	2.65	0.93	0.89
Jackson	1.08	0.56	0.57	0.84	0.84	0.52	0.53	0.77	0.78
Jefferson	0.31	0.40	0.41	0.35	0.36	1.29	1.33	1.14	1.15
Leon	0.19	0.76	0.31	0.12	0.12	3.89	1.61	0.60	0.62
Liberty	1.03	1.08	1.53	2.82	2.82	1.04	1.49	2.73	2.74
Okaloosa	0.29	0.22	0.54	0.34	0.33	0.75	1.89	1.17	1.16
Santa Rosa	0.68	0.32	0.23	0.28	0.27	0.48	0.34	0.41	0.40
Wakulla	0.72	0.61	0.70	0.76	0.76	0.85	0.97	1.05	1.06
Walton	0.34	0.28	0.30	0.42	0.43	0.83	0.88	1.25	1.27
Washington	0.53	0.36	0.35	0.33	0.34	0.69	0.66	0.63	0.64

Notes: SF=Step-Forward, PVAR1= Panel VAR with three endogenous variables, PVAR2= Panel VAR with four endogenous variables.

the MASE value, the more preferred the autoregressive models over the simple step-forward method. According to the MASE values, most of the series showed at least slight improvement from using the standard VAR. The best cases corresponded to Santa Rosa and Jackson counties with MASE close to 50 percent, which translates into the VAR having close to half the forecast error of the simple forecast. The use of the FAVAR and Panel VAR further improved the forecast, over the step-forward method. Once again, the results showed a mixed trend across counties with some counties displaying larger gains from the use of one method over another. Liberty and Holmes proved the exception, with both counties showing no improvement in forecast accuracy across all VAR models used.

Graphic representation of the VAR forecast against the observed values in Figure III.4, however, show that the forecast accuracy varied across the forecast years. Santa Rosa's forecast, for example, revealed a forecasted value close to the observed value during the last period. The intermediate years however showed values farther apart. In general, the plotted forecasts revealed the VAR prediction for the first period (2007), at least having the same direction as the actual observation, than subsequent forecasts periods. Similar trends can be observed in the forecast graphs for the FAVAR and PVAR specifications shown in Figures III.5 and III.6, respectively. Comparing the graphs for the VAR and FAVAR forecasts, we observed only a few counties, such as Okaloosa and Escambia, displaying slight differences while the majority showed no apparent differences in the forecast. The PVAR models on the other hand displayed a more irregular pattern with the forecast moving in opposite directions to the observed value. The two specifications (PVAR1 and PVAR2) moved close together across the majority of the counties. This similarity in the forecasts indicates a minimal gain from the addition of the extra

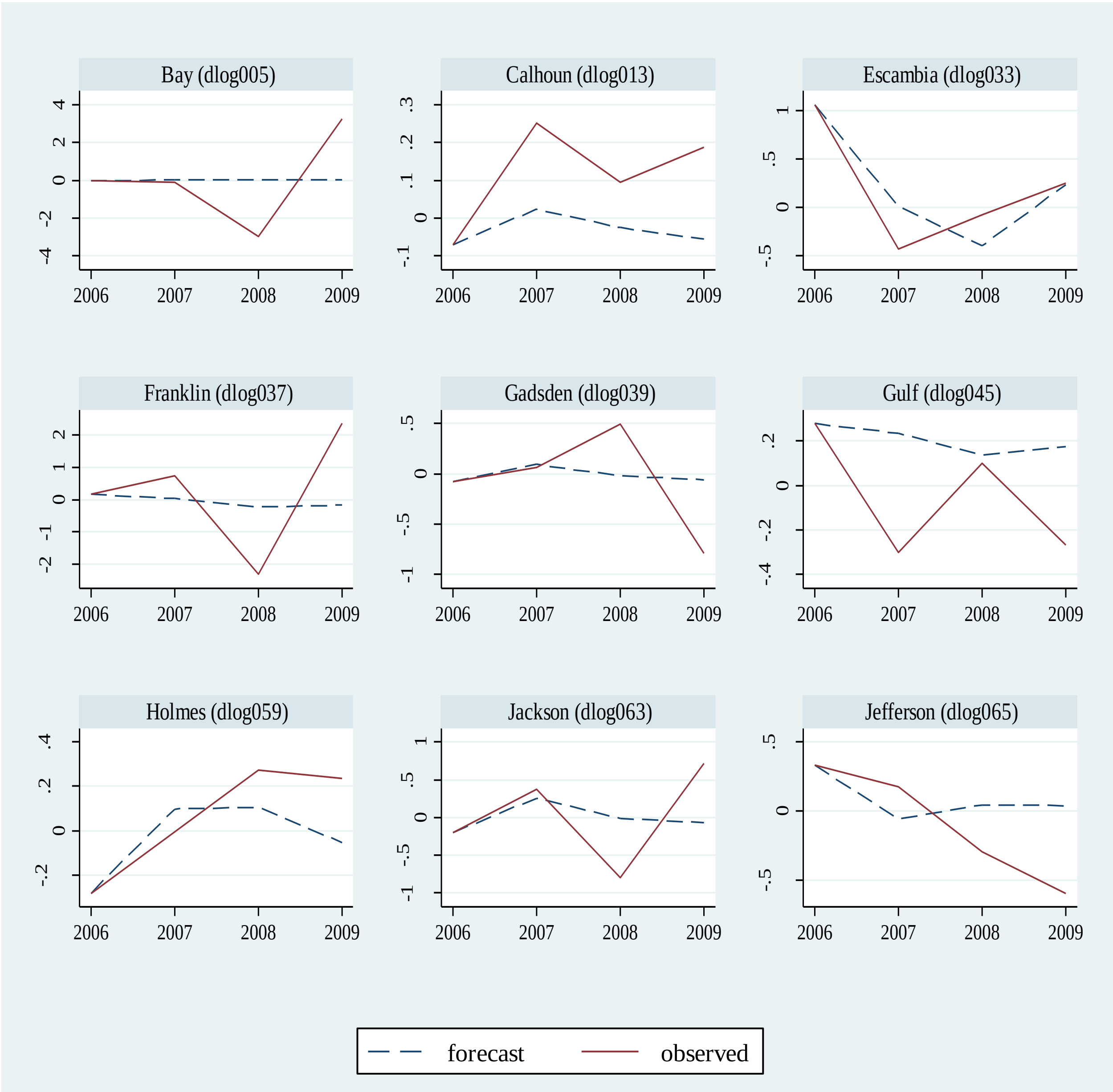
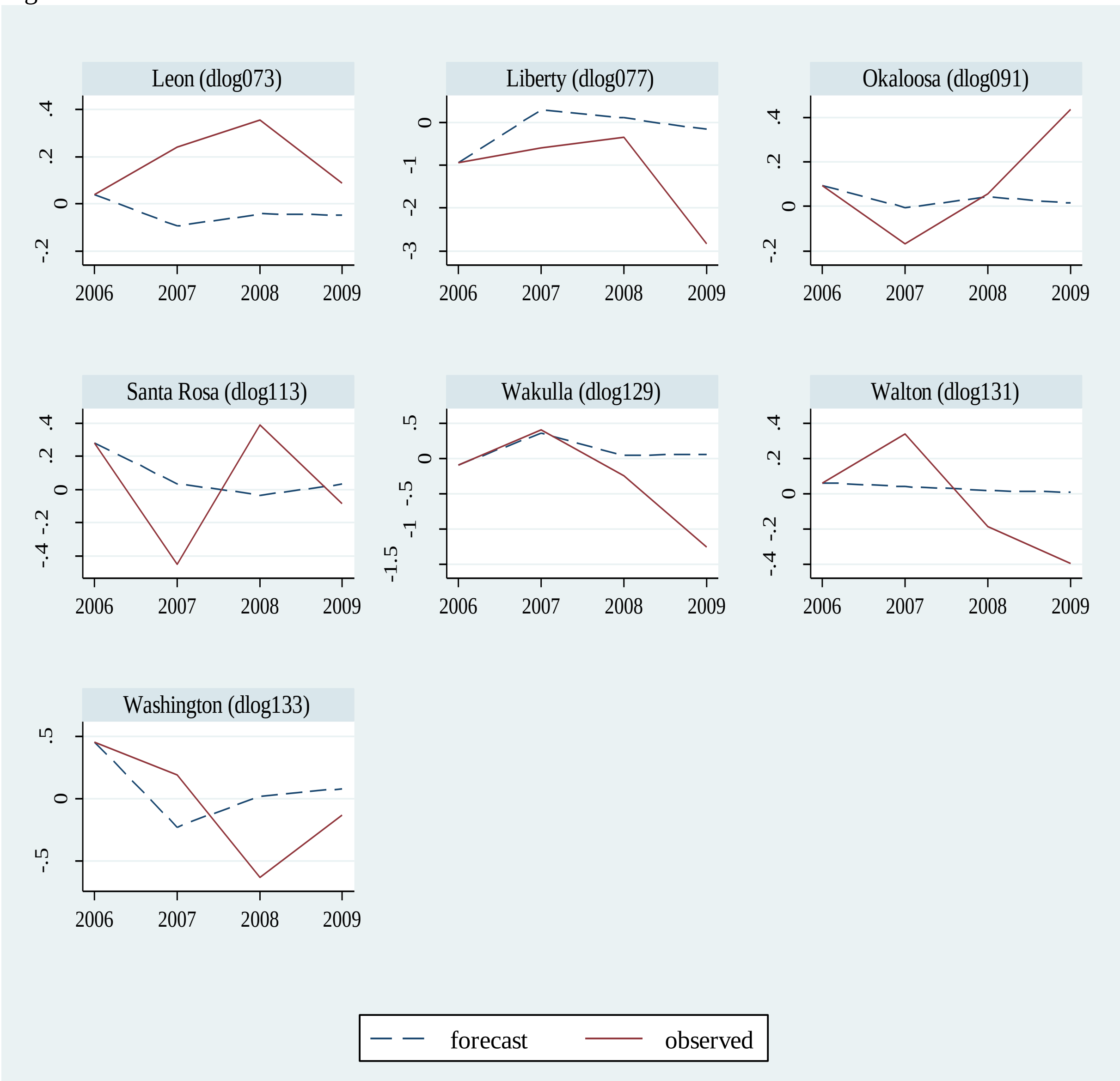


Figure III.4 Forecast values for county pulpwood production, VAR specification against the observed values.

Figure III.4 Continued



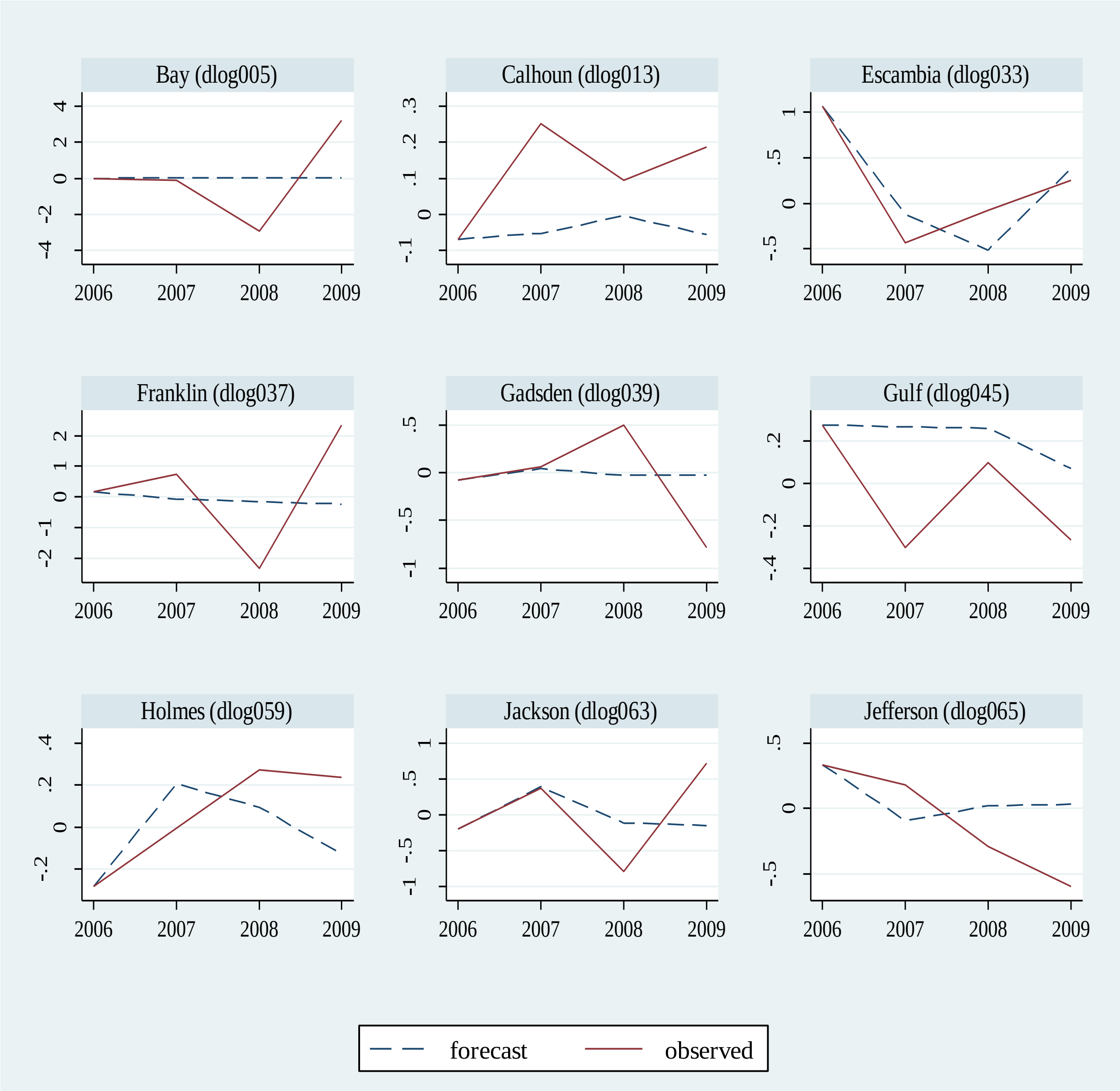
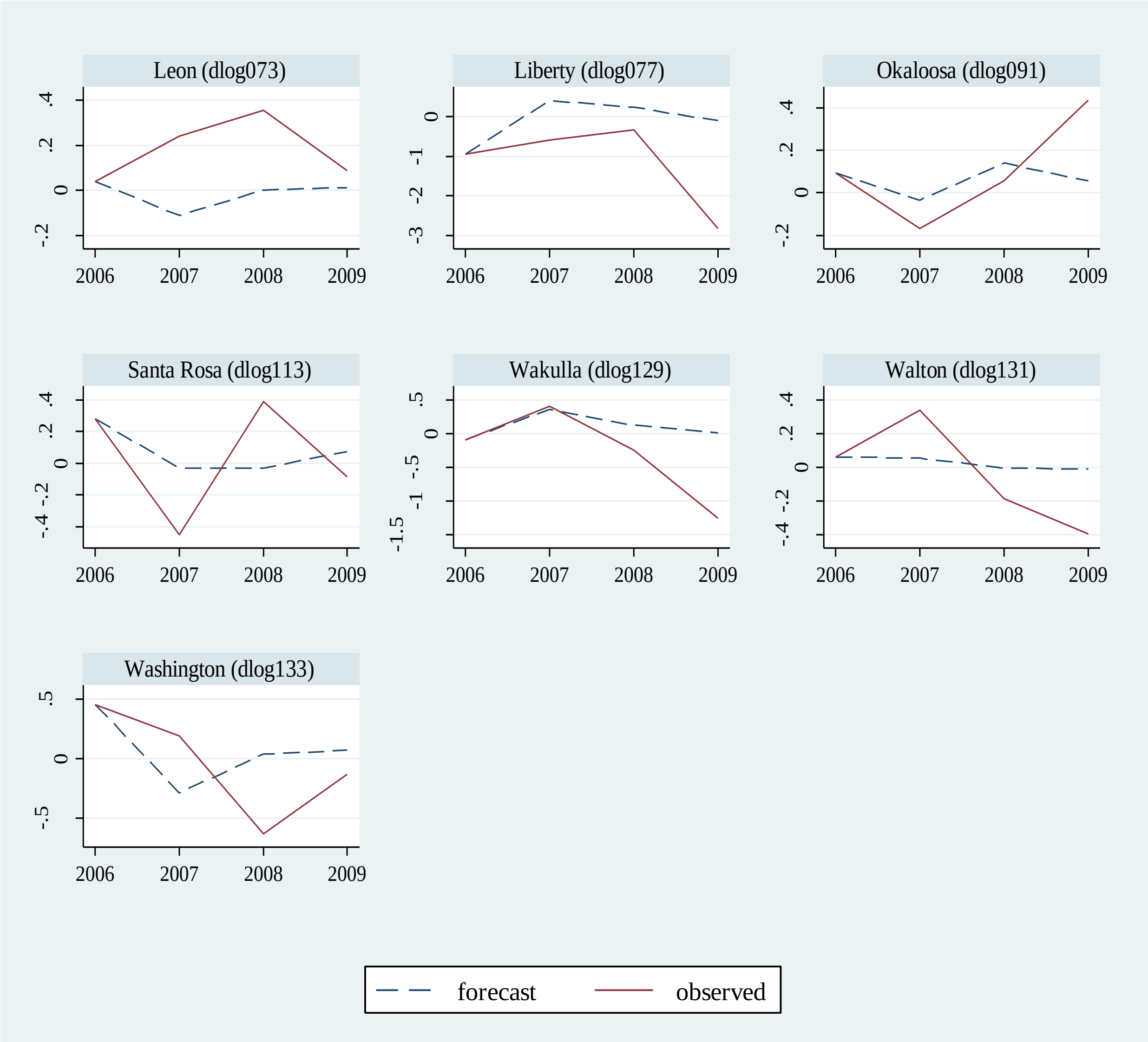


Figure III.5 Forecast values for county pulpwood production, FAVAR specification against the observed values

Figure III.5 Continued



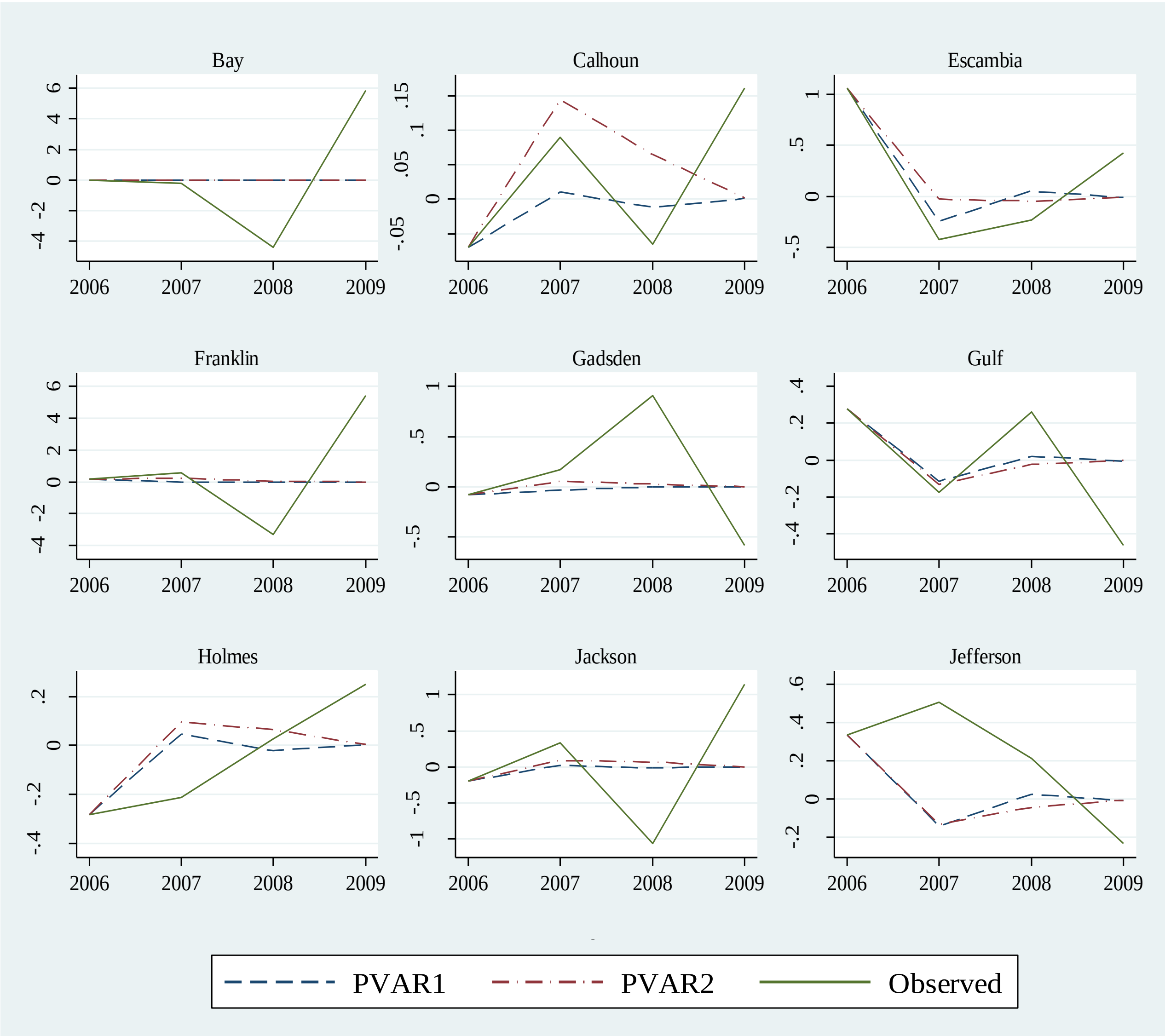
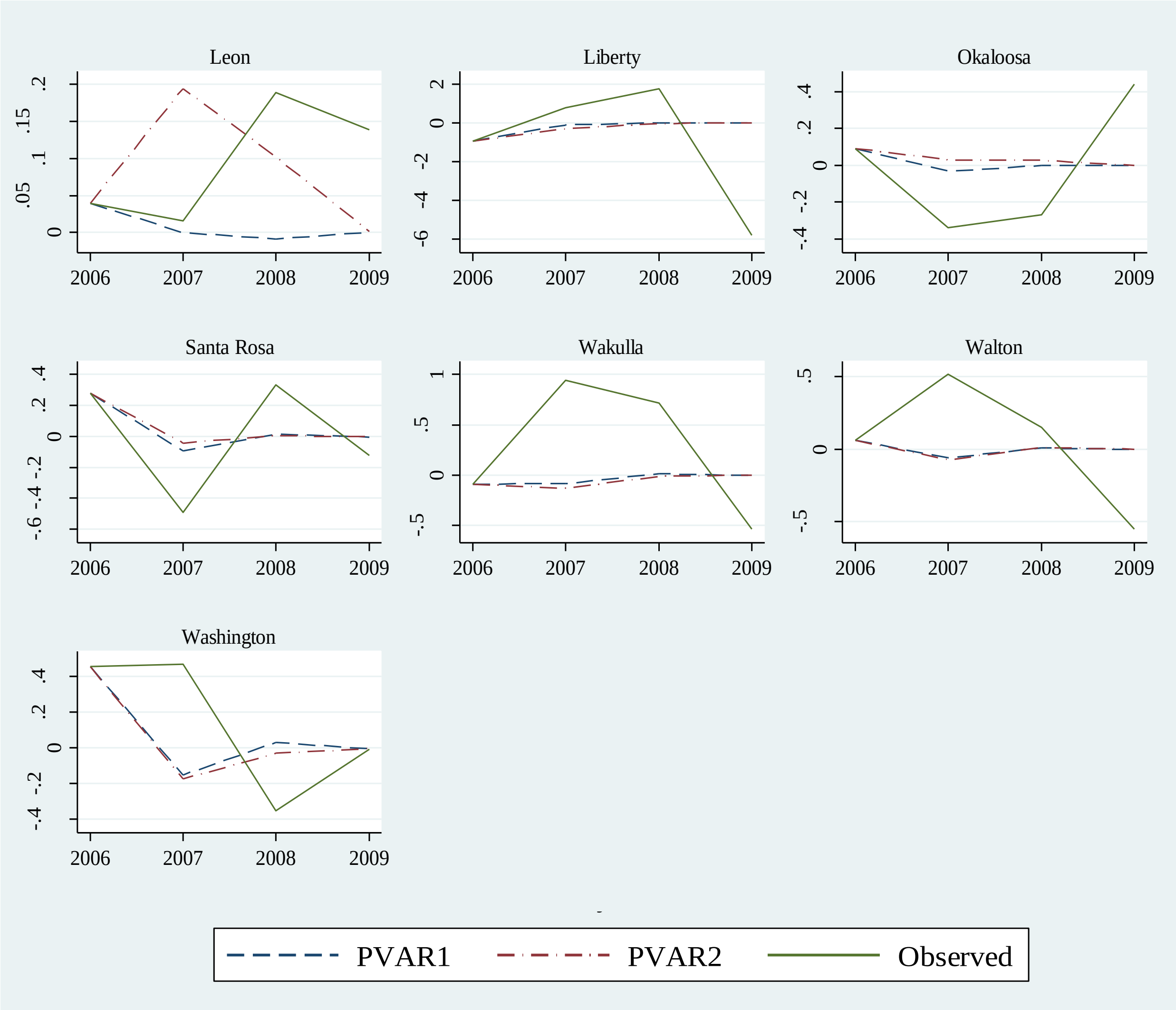


Figure III.6 Forecast values for county pulpwood production, PVAR specifications against the observed values.

Figure III.6 Continued



endogenous variable in PVAR2. Similar to the VAR and FAVAR forecasts, the PVAR showed better performance in the forecast of the first period, although not in all counties. While the PVARs forecast for Escambia and Gulf, for example, revealed some similarities between forecast and observed values, we can see Walton and Wakulla counties showing no resemblances between forecast and observed.

7. Conclusions

The research presented in this chapter explored the characteristics of wood procurement time series for a group of Florida counties. Using these time series, we evaluated the performance of VAR models to forecast future timber production at the county level given macroeconomic variables. We utilized data from 16 Florida counties corresponding to the northwest FIA survey unit. As a whole, this unit provides a substantial part of Florida's total timber output. Among others, the ability to forecast or predict future movements of wood in a county given general economic conditions can provide timely information to forest managers and state agencies. Such information can assist agencies targeting assistance or policies towards forests resource management.

Initial examination of the data revealed a mixed picture. Pulpwood volume did not follow the GDP trends as closely as expected. Inclusion of the Producers Price Index as a proxy for national pulpwood prices improved the performance of the VAR. However, overall, the macroeconomic variables did not appear to capture the dynamics of county pulpwood procurement. Nonetheless, the VAR models provided a better alternative for forecasting when compared to a simple step forward forecasting approach. One must be cautious, however, as the family of VAR models evaluated proved effective only on a portion of all counties. In effect, the data showed the flow of pulpwood differing considerably across counties and across time. As a consequence, applying the same VAR specification to all counties would fail to capture the varying conditions of the pulpwood procurement series. Future research needs to identify the underlying reasons for these differences among counties. Forest resource characteristics seem a likely source for county heterogeneity. Although the FIA forest inventory provides information to identify the forest resources of the area, the disaggregation to county levels would bring high levels of error due to the sample intensity. Nonetheless, methods to incorporate forest inventory information into the VAR analysis need to be evaluated. Possible ways to capture forest resources include the use of a weight, based on county area relative to an FIA unit, or the use of imagery to determine forest cover area for each county. Similarly, the analysis of the pulpwood series revealed the presence of structural breaks for all counties. For some counties, the external shock resulted in a change in trend direction and intensity. Further investigation of these breaks in terms of nature and expected effects is needed. Such information would aid determine the procurement areas expected response to future similar external shocks.

In summary, the effectiveness of the VAR approach should be evaluated county by county and alternative methods utilized to predict series movement for counties that show a low correspondence with macroeconomic variables. Results from the forecast research provide information to guide future TPO forecasting practices. Although the forecasting performance of the tested VAR was not optimal, the exercise provided evidence of the large errors associated with a simple step forward methodology. Further, the VAR methodology showed the potential improvement in accuracy to be gained from a formal specification. Further research could explore a combined approach between the FAVAR and PVAR, to exploit the gains in sample size from the panel together with the gain in information from the factor-augmented specification.

IV Summary and Conclusions

Timberlands have economic significance beyond the monetary value of the growing timber. Environmental, aesthetic, recreational, and cultural values have not been a direct part of the market value of timber but instead have been indirectly addressed through individual preferences or regulations and policies. For example, private landowners consider non-timber services such as recreation or aesthetics when making harvesting decisions; environmental regulations and management policies increase timber harvest costs and allow for fragile areas to be withdrawn from production. Because forests provide a number of ecological services, the public benefit from adequate forest management in private lands is significant. Adequate forest management can also ensure the necessary supply of timber products to satisfy the nation demands and lessen the dependence on foreign resources. Additionally, maintaining a sustainable supply of wood help maintain the industry, supporting rural economies.

In this light, the research developed in this dissertation investigated the relationship between primary mill demand and procurement areas. The first essay evaluated the effect of available mill markets on the likelihood of private forest landowners to engage in forest management activities. For the analysis, we applied multivariate probit models to data from the USDA Forest Service Forest Inventory and Analysis forest inventory and Timber Products Output. In this manner, we combined data for forest management at the FIA plot level with data from mill surveys which provide mill location and volume of mill receipts. Results from our analysis contradict the common belief that mill proximity will motivate management. In effect, only sawmills significantly affected the management decision and with a relatively low effect. Overall, the study points to the need for mechanisms other than mill demand to encourage management in private non-industrial forest lands. The analysis also revealed a low probability of regeneration following harvest of a single species (between 25 and 35 percent), and a lower probability of management in hardwood stands.

In our second study we examined the use of a VAR methodology to forecast mill procurement at the county level. Understanding the dynamics of timber flow can assist in planning of management activities. Movement of timber forms a vital part in the analysis of resource use and sustainability. The TPO dataset provides a wealth of information that can help predict future timber flows. The VAR analysis revealed the need for a county-to-county evaluation and the need to further explore other macroeconomic series that might bring a better fit. The initial outcomes give promise to a straightforward methodology to forecast the flow of pulpwood volumes.

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Appendices

Appendix A - Specification tests results and output tables from single probit regressions.

Table A-1 Probit specification tests and mean variance inflator (VIF).

Test	Harvest hardwood	Harvest softwood	Regeneration	Timber stand improvement
		--- *Prob > chi2* ---		
Lagrange multiplier test normality	0.9726	0.6361	0.6048	0.3941
Wald test of Homoskedasticity	0.2791	0.1576	0.7769	0.7025
Wald test of exogeneity*	0.0641	0.2505	---	0.0985
Mean VIF	2.10	1.94	2.21	2.18

Notes: *= Suspect endogenous variables include plot's proportion of softwood and stumpage prices.

Table A-2 Probit regression, softwood harvest outcome.

Variables	Coefficient	Standard Error[1]
delta	0.1955***	(0.039)
t	-0.1532***	(0.032)
oper	-0.0608	(0.123)
lnstand	-0.0206	(0.034)
propswd	0.6573***	(0.132)
gs01	0.0059	(0.035)
land_dac	-0.0000	(0.000)
miles_town	0.0122	(0.011)
ppsqm	-0.0013	(0.001)
percinc	0.0370*	(0.022)
pop65	-0.0062	(0.040)
unit2	-0.3167*	(0.179)
unit3	0.3396**	(0.154)
wsst	0.0083*	(0.004)
wsply	0.0011	(0.003)
ssaw70	0.0560**	(0.022)
sply70	-0.0731	(0.082)
spw100	0.0588	(0.051)
Constant	-3.7288***	(0.792)
Log Pseudo-likelihood	-388.273	
Pseudo R-squared	0.1837	
Observations	1,560	

Notes: [1] = Errors adjusted for 780 clusters in plot id.
***= significant at 1%, **= significant at 5%, and *=significant at 10%.

Table A-3 Probit regression, hardwood harvest outcome.

Variables	Coefficient	Standard Error[1]
delta	0.1580***	(0.037)
t	-0.1704***	(0.033)
oper	0.0896	(0.121)
lnstand	-0.0324	(0.035)
gs01	0.0417	(0.035)
land_dac	-0.0000	(0.000)
miles_town	0.0035	(0.012)
ppsqm	-0.0022**	(0.001)
percinc	0.0332	(0.022)
pop65	-0.0791*	(0.042)
unit2	-0.3016*	(0.164)
unit3	0.2332	(0.144)
hsaw70	0.0817***	(0.029)
hpw100	0.1010	(0.079)
propswd	0.4384***	(0.127)
whst	0.0029	(0.015)
whpw	-0.0412	(0.048)
Constant	-1.9330***	(0.654)
Log Pseudo-likelihood	-366.504	
Pseudo R-squared	0.1629	
Observations	1,560	

Notes: [1] = Errors adjusted for 780 clusters in plot id.
***= significant at 1%, **= significant at 5%, and *=significant at 10%.

Table A-4 Probit regression, regeneration outcome.

Variables	Coefficient	Standard Error[1]
oper	-0.3792***	(0.134)
delta	0.2936***	(0.066)
t	-0.1941***	(0.045)
lnstand	0.0117	(0.035)
low_site	0.4123	(0.252)
med_site	0.4795**	(0.189)
medh_site	0.4883**	(0.192)
gs01	0.0873**	(0.040)
acres_chg	0.0845	(0.228)
land_dac	-0.1000	(0.000)
miles_town	-0.0059	(0.012)
ppsqm	-0.0010	(0.001)
percinc	-0.0128	(0.025)
pop65	-0.0506	(0.053)
unit2	0.0986	(0.172)
unit3	0.1422	(0.167)
wsst	0.0091*	(0.005)
whst	0.0355*	(0.019)
hsaw70	-0.0158	(0.042)
ssaw70	0.0015	(0.031)
hpw100	0.0786	(0.087)
Constant	-2.2318**	(0.924)
Log Pseudo-likelihood	-326.638	
Pseudo R-squared	0.209	
Observations	1,560	

Notes: [1] = Errors adjusted for 780 clusters in plot id.
***= significant at 1%, **= significant at 5%, and *=significant at 10%.

Table A-5 Probit regression, timber stand improvement outcome.

Variables	Coefficient	Standard Error[1]
oper	-0.5075**	(0.206)
delta	0.0637	(0.045)
t	-0.1121**	(0.045)
lnstand	0.1715***	(0.046)
propswd	0.4266**	(0.199)
low_site	-0.2671	(0.298)
med_site	-0.5506***	(0.207)
medh_site	-0.3685**	(0.185)
gs01	0.0177	(0.044)
acres_chg	0.8212**	(0.324)
land_dac	0.0000	(0.000)
miles_town	0.0071	(0.015)
ppsqm	-0.0031**	(0.001)
percinc	0.0420	(0.038)
pop65	-0.1470***	(0.057)
unit2	-0.3922	(0.245)
unit3	0.5181***	(0.192)
wsst	0.0085	(0.007)
whst	-0.0402*	(0.024)
hsaw70	0.0876*	(0.045)
ssaw70	-0.0131	(0.035)
hpw100	0.1253	(0.104)
Constant	-2.0862**	(1.032)
Log Pseudo-likelihood	-171.661	
Pseudo R-squared	0.1724	
Observations	1,560	

Notes: [1] = Errors adjusted for 780 clusters in plot id.
***= significant at 1%, **= significant at 5%, and *=significant at 10%.

Appendix B - Variables used in the Factor Analysis.

Table B-1 Factor Analysis, list of variables with description and data sources.

Variable	Description	Units	Movement
GDPI	Gross private domestic investment	index	Slow
PC_Exp	Personal consumption expenditures	index	Slow
Empl	All employees, non-durable goods	thousands of people	Fast
CPI_Urb	Consumer price index, urban	index	Slow
TB3M	Interest rate 3-month Treasury Bill	percent	Slow
PPI_fuel	Producer price index fuel/power	index	Slow
PPI_lumber	Producer price index lumber	index	Fast
IC_paper	Industrial production capacity, paper	index	Fast

Source: Federal Reserve Bank of St Louis (2012).

Appendix C - List of Stata User-Written Commands used.

COMMAND (year created), Author(s)

Description (Reference to associated paper)

MVPROBIT (2003), Lorenzo Cappellari and Stephen P. Jenkins.

Calculate multivariate Probit regression using simulated maximum likelihood (Cappellari & Jenkins, 2003).

MVDRAWS & **MVNP** (2006), Lorenzo Cappellari and Stephen P. Jenkins.

Calculate multivariate normal probabilities by simulation (Cappellari & Jenkins, 2006).

SKPROBIT (2010), Diallo Ibrahima Amadou.

Perform Lagrange multiplier test for normality for the Probit model (Amadou, 2010).

IVREG2 (2002), Christopher F Baum, Mark E Schaffer and Steven Stillman.

Extended instrumental variables/2SLS and general method of moments (GMM) estimation (Baum, Schaffer, & Stillman, 2007).

GHANSEN (2011). Jorge Eduardo Perez Perez.

Perform the Gregory-Hansen test for cointegration with regime shifts (Perez, 2011).

PVAR (2009), Inessa Love.

Estimate a panel vector autoregressive model as described in Holtz et al. (1988) (Love & Zicchino, 2006).

Vita

Consuelo Brandeis was born in Santiago, Chile. She graduated with a Bachelor's degree in forest engineering from the University of Talca Chile in 1994. She moved to Corvallis, Oregon in 1996 where she worked for a local timber services company for two years before accepting employment at the Oregon State University's College of Forestry. In 2001 Consuelo moved to San Juan, Puerto Rico where she resided until 2003. While in Puerto Rico, she worked for a local non-profit, the Puerto Rican Conservation Foundation, as an independent contractor and started pursuing her Master's Degree through the University of Denver's distance education program. Consuelo moved to Knoxville, Tennessee, in 2003 where she worked for the University of Tennessee Research Office while continuing her studies. She graduated from the University of Denver program with a Master's in Environmental Management in 2007. She started her Ph.D. program at the University of Tennessee under the University's Diversity Scholarship. In 2009, Consuelo accepted a position as part of the Student Career Experience program with the USDA Forest Service, Forest Inventory and Analysis program, Timber Products Output group. Upon graduation she will take a full time position as a research forester with the Knoxville FIA research work unit.