RESEARCH ARTICLE

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Analysis of North Carolina Forest Industry Earnings: Adapting Household-Level Data from the American Community Survey to a Social Accounting Matrix

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There is a significant need to not only understand how different industries contribute to overall wealth but how they affect certain segments of society. This study augments input-output social account matrix (SAM) modeling techniques with American Community Survey (ACS) Public Use Microdata Samples (PUMS) to better characterize North Carolina forest products industry earnings' impact on low-, medium-, and high-income households. A 2014 North Carolina SAM was created using IMpact Analysis for PLANning (IMPLAN) and customized so that industry-specific earnings were allocated to household income classes according to the distributions contained within the ACS-PUMS data set. Multipliers were determined to describe earnings distributions per dollar change of final demand. These multipliers were then contextualized by perturbing the SAM model with a 10% change in final demand for relevant forest product industries. The results of the analysis indicate that SAM analysis methods based on unmodified IMPLAN models underestimate earnings paid to low-income and overestimate earnings paid to high-income households resulting from economic growth in the study area. Scenario results obtained using our updated SAM model highlight the improved analytical capabilities of this approach for measuring impacts across income class.

Keywords: input-output analysis, social accounting matrix, forest products, income distribution analysis, North Carolina

The influence of policy decisions on household income inequality within a geographical region has been of interest to economic analysts for a long time. Potentially differing impacts between groups is important when a policy is designed to promote a particular industry as a tool for regional economic growth. Multiple studies have investigated the impacts of natural resource industries such as tourism, fisheries, and forestry on regional economies to determine if their growth could increase wages in lower-income households (Hughes and Vlosky 2000, Hughes and Shields 2007, Arita et al. 2013). Findings from these studies vary and depend on the industry segment, regional economic structures, average regional wages, and household-level decisions regarding labor force participation. However, these studies also highlight different methods that may be used to quantify the influence of industry growth on household income.

Many options are available for estimating economic impacts resulting from economic growth or policy efforts. Three popular approaches include the application of a regional input-output (I-O) model, a social accounting matrix (SAM), or a computable general equilibrium (CGE) model. It is reasonable to ask which of these models is most appropriate. In an effort to determine which model provides the best results, Van Wyk et al. (2013) compared the three methods using a similar demand shock across all models, and substantial differences between model results were observed. The SAM provided the largest estimate of generated impacts whereas the CGE estimated a smaller, more conservative overall impact. Recognizing that different models have different strengths and weaknesses, decisions about which model is most appropriate for a given research question depend on data availability, the size of the region being modeled, the level of complexity required to answer the research question, and the specific research question being asked. When interested in investigating the influence of a demand

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shock on household wages and earnings, SAM models have emerged as the historically preferred technique (Leatherman and Marcouiller 1996, Hughes and Vlosky 2000, Arita et al. 2013).

Quantifying the relationship between industry growth and household income has been of particular interest for those promoting tourism as a tool for regional economic development. Hughes and Shields (2007) reviewed the literature and provided insights into who receives the benefits of tourism growth, pointing out that results are mixed. Advocates of tourism as a tool for economic development highlight job creation and the resulting direct and indirect impacts. Critics tend to stress that these jobs are often low-skilled, low-wage positions that are often seasonal (Fleischer and Pizam 1997, Wagner 1997). Conflicting results may be expected when making cross-study comparisons because there are likely to be substantial differences in regional supply chains and purchasing patterns of local goods and services. In particular, their article investigated tourism as a "hollowing out" industry, a phenomenon used to describe an industry that pays wages to high-income proprietary business owners and their low-income, low-skilled, employees while creating minimal opportunities for medium-income-type jobs. Identifying who receives the benefits of economic growth is important in driving policy discussions related to economic development. This could be critical in defining the contribution of forest-based industries to regional economies and their households.

Past research by Rose et al. (1988) emphasized the need to identify winners and losers associated with natural resource policy, not just net benefits. Their work pointed out that natural resource policy has the most immediate impact on rural citizens and economies, which are often associated with high levels of poverty. Increased economic activity resulting from resource extraction may increase overall regional per capita income, but not necessarily for all households. This is because economic gains can often flow to potentially absent landowners while the resources are exported, creating only backward-linked growth opportunities. In addition, negative impacts such as pollution can disproportionally affect households in lower-income brackets (Rose et al. 1988).

Sorenson et al. (2016) provided a regionally specific estimate of direct job creation and annual wages paid by forest product industries within the United States. By observing the relationship between wage and employment impacts per unit of timber harvested, their study investigated the influence of geographical terrain, timber quality, and timber volume in determining the number of employees that are required to harvest timber in different regions. Sorenson et al. (2016) concluded that the long harvesting season, gentle terrain, and homogenous timber quality characteristic of southeastern states allowed for higher volumes of timber to be removed by fewer employees. Their study also revealed the role of mill specialization and automation within primary processing facilities and how these factors might influence direct employment. They point out that the large, capital-intensive pulp and paper mills in the Southeast employ fewer people per unit of output and pay higher wages than their Northeast counterparts. Although this study provides conservative estimates of job and wage creation resulting from timber harvests, Sorenson et al. (2016) did not try to draw any conclusions regarding how the economic impacts of industry earnings[1] were distributed across households with differing income levels.

Researchers commonly use the SAM to investigate how industry earnings are distributed to households. The SAM illustrates the circular flow of income in a region and can be used to investigate the distributive impacts of a policy change across different household income classes and determine differences in benefits (Pyatt and Round 1985, Stone 1985, Round 2003). These regionally based SAM data tables provide detailed information regarding the differences in production sector supply-chain requirements. Among other attributes, these SAM tables can be stratified by place of work (rural versus urban), proficiency level (unskilled versus skilled), and income level (low, medium, and high). As Leatherman and Marcouillier (1999) point out, the composition of an industry supply chain can yield different returns to households depending on where factor inputs are purchased and if workers re-spend their wages within the regional study area. Typically, the SAM modeling approach investigates an individual sector's contributions to household earnings while also recognizing that a large sector output does not necessarily maximize local income.

Economic impact analyses conducted using SAM models are often performed using IMpact analysis for PLANning (IMPLAN). IMPLAN is a software package that combines regionally specific data with IO and social-accounting techniques to estimate the economic impacts associated with an "event" (e.g., a private or public investment or policy change; IMPLAN Group, LLC, 2017). Developed in the 1970s to assist the US Forest Service in assessing the impact of forest management plans on local communities, it has evolved to include all industrial segments using data from the Bureau of Labor Statistics, the Bureau of Economic Analysis (BEA), the US Department of Agriculture, and others. Economic models describe specific industrial segments and geographies of varying size (e.g., county, multicounty, state, or multistate level). Where data gaps exist, statistical methods are applied to compile a regional SAM consisting of 536 industrial sectors. Using this model, analysists estimate the economic impacts of an event based on regionally specific

Management and Policy Implications

Policymakers often turn to input-output analysis for generating employment and economic impact estimates. This economic modeling technique is a valuable tool for describing the role that an industry plays within a regional economy and predicting the results of economic change. This research suggests that the modeling technique may be improved by incorporating American Community Survey Public Use Microdata Sample data sets into regional economic models. These data sets provide valuable regional demographic data that describe how different industries pay their employees and how those earnings contribute to overall household income. By incorporating these data sets, economic models can describe which households receive the benefits of industry growth. This information is crucial for policymakers who are interested in facilitating economic development and creating opportunities for upward mobility for low- and middle-income households within their region. Analysts can then compare economic scenarios and analyze results with respect to households in differing income brackets. Thus, the goal of this study is to provide policymakers with more detailed information about the economic impact of natural-resource-based policy change on household earnings.

supply chains structures and consumer spending (Day n.d.).

Traditionally, IMPLAN SAM models describe payments to households using what is commonly referred to as the "brain-dead SAM," an extended IO model that includes household activities (receipts and payments) when deriving economic multipliers. The brain-dead SAM places all industry payments for employee compensation and proprietor income into a common pool. From this aggregate pool, payments are distributed to one of nine household income levels on the basis of fixed income shares (Hughes and Vlosky 2000). This brain-dead SAM is defined so because it "lacks the ability to examine how industries with different factor intensities are explicitly linked to households broken down by socioeconomic classes" (Arita et al. 2013). Although aggregating these two forms of payment provides a regional average that describes industry payments for labor, such aggregation ignores the fact that household earnings distributions can differ drastically from industry to industry. What results is an oversimplified distribution of household earnings based on a regional average across all of the different industrial sectors.

Industries, particularly those dependent on natural resources, are known to have varied wage structures. These varied wage structures make the brain-dead SAM less useful for estimating the impacts of economic changes on household earnings (Hughes and Vlosky 2000, Arita et al. 2013). Limitations of the brain-dead SAM are overcome by linking individual industry earnings to household income classes using an industry occupation matrix. These matrices report average earnings for different occupations within an industry using regionally specific data from state and federal sources. Earnings data are then assigned to household income groups based on the industry occupation matrix, a SAM submatrix. Studies using the industry occupation matrix found that industry earnings by income class vary according to the occupational needs of their respective study regions.

Hughes and Shields (2007) concluded that using an industry occupation matrix to link individual earnings to households may be problematic when considering the role of secondary employment on total household income. As is commonly the case, multiple individuals with varied careers may contribute earnings to a single household, or an individual within a household may also work more than one job. Classifying each job within each industry to a single household income class ultimately results in the assumption that each wage earner is the sole breadwinner for a household. Although the industry occupation matrix can be useful for describing a distribution of knowledge, skills, and abilities within and between industries via occupational wage earnings, its use is more limited when extended to the household as an economic unit. For our study, this limitation was overcome by using state-specific data provided by the 2014 American Community Survey (ACS) Public Use Microdata Sample (PUMS) in our analysis.

The ACS is an ongoing survey administered by the US Census Bureau that provides an annual portrait of economic activities of all US communities. The survey asks questions regarding a respondent's demographic, social, and economic characteristics. These responses are tabulated at individual and household levels. Access to these ACS responses are provided via PUMS data sets. Annually updated PUMS data sets represent approximately 1% of the US population and are available at the state level through the US Census Bureau website (US Census Bureau 2014). These data sets offer researchers the opportunity to analyze ACS responses and obtain information not previously offered through pretabulated ACS products, thus giving researchers flexibility in analyzing data based on their research question.

The purpose of this study is to investigate how industry earnings generated from employment in North Carolina's forest products industries are distributed to different household income levels. We use SAM modeling techniques, augmented with regionally specific PUMS data, to determine how employee compensation and proprietor income are distributed to households. Using our customized SAM model, we then used household earnings multipliers classified by income level to describe how changes in economic activity influence the wages and salaries paid by industries to households with differing income levels. Finally, we compare our results to those generated using the traditional brain-dead SAM modeling techniques and compare the two approaches.

Study Methods

A SAM model was constructed in IMPLAN version 3.0 using North Carolina's 2014 data set and is represented in Equation 1 (Holland and Wyeth 1993). Submatrix A described interindustry transactions. Submatrix V described value-added payments from industries to employee compensation, proprietor income, property income, and taxes on production and imports categories. Value-added contributions to households were described in submatrix Y. Household consumption patterns were described in submatrix C. Lastly, distributions of employee earnings to households were described in submatrix H.

$$SAM = \begin{bmatrix} A & 0 & C \\ V & 0 & 0 \\ 0 & Y & H \end{bmatrix} \quad (1)$$

The model's 536 sectors were aggregated to 48 sectors (categories) on the basis of the North American Industry Classification System three-digit classification system, which is then matched to the employment information found in the PUMS data set. Forest products-related industries were aggregated according to Appendix Table 1. Model output for the forestry sector was customized to reflect delivered wood values at the time on the basis of North Carolina Cooperative Extension surveys (Jeuck and Bardon 2014). As recommended by Holland and Wyeth (1993), IMPLAN model estimates for employee and proprietary compensation were replaced collectively with 2014 BEA (Bureau of Economic Analysis 2014) personal income by major component data provided in Table SA5N.

$$reduced\ SAM = \begin{bmatrix} A & C \\ L & H \end{bmatrix} \quad (2)$$

Because the brain-dead SAM approach inadequately described how industry earnings were distributed to households, we created a reduced SAM, represented in Equation 2, following a process described by Holland and Wyeth (1993). The reduced SAM represented households who received their income directly from industries, redistributing the components of value added represented in submatrices V and Y. Labor income components of value added were redistributed to submatrix L on the basis of household earnings by industry distributions. These distributions represented how industry wages and salaries were distributed to different household income levels. Taxes associated with employee compensation and proprietary income were reallocated to exogenous institutional accounts on the basis of an industry output weighting scheme. Nonearnings components of value added were included in the model but were also treated as exogenous accounts.

Industry earnings reported by the BEA were distributed to submatrix *L* on the basis of the industry to household income distributions previously mentioned. Distributions were created using data provided by the North Carolina 2014 PUMS data set, representing the full range of population and housing unit responses to the ACS. North Carolina's 2014 PUMS data set consisted of 97,830 respondents dwelling in 44,466 households. Using this data set, individual sample respondents were assigned to both a household and an industry, with each household falling into an income category on the basis of wage and nonlabor household income. We maintained IMPLAN's default of nine household income classes, which were further aggregated into low, medium, and high levels of income. Low-income households were defined as having a total annual income less than $35,000. Medium-income households had a total annual income falling between $35,000 and $100,000. High-income households received more than $100,000 each year. Income-level classifications were based on classes used in a recent distributive impact study (Arita et al. 2013). Earnings distributions were created for each industry from the PUMS data set by summing wages paid to an individual household income level and dividing this sum by the total wages paid to all households for that industry. These distributions were then applied to BEA earnings estimates and entered into the SAM, providing a description of how industry wages were distributed to the multiple household income classes.

After creating the reduced SAM with industry contributions allocated directly to households, it was necessary to rebalance the matrix using a biproportional scaling technique to force consistency between row and column totals (Miller and Blair 2009). The column sums, which reflected the addition of customized logging output and BEA earnings by industry, served as our new control totals. Sixteen iterations were completed to force the row and column totals to consistency, which is a fundamental requirement for SAM analysis.

Following the SAM model balance, the Leonteif Inverse was applied to the reduced SAM following traditional methods with interindustry and household linkages treated as endogenous accounts. A matrix of normalized expenditure shares (*S*) was created by column-normalizing SAM matrix elements by their respective column totals, described in Equation 3. The *S* matrix was then subtracted from its respective identity matrix to form the (*I-S*) matrix. The (*I-S*) matrix was then inverted, creating the SAM inverse matrix described in Equation 4. Following the application of the Leontief Inverse, total effects and household earnings by industry multipliers were created for each industry by summing the necessary coefficient components.

$$S = \frac{z_{ij}}{X_j} \tag{3}$$

$$SAM\ Inverse\ Matrix = (I - S)^{-1} \tag{4}$$

To contextualize the multipliers that we created, an impact analysis was performed on our customized North Carolina 2014 SAM model, referred to in the text below as NCFOREST. Final demand increases equivalent to 10% of industry output were applied to our model's five relevant forest product industries. These results are then compared alongside an "out-of-the-box," ready-made, but brain-dead, SAM, which was not augmented with industry-specific regional income data. The difference in results between the two models was examined to determine how our customized model offered improvement over the brain-dead model approach.

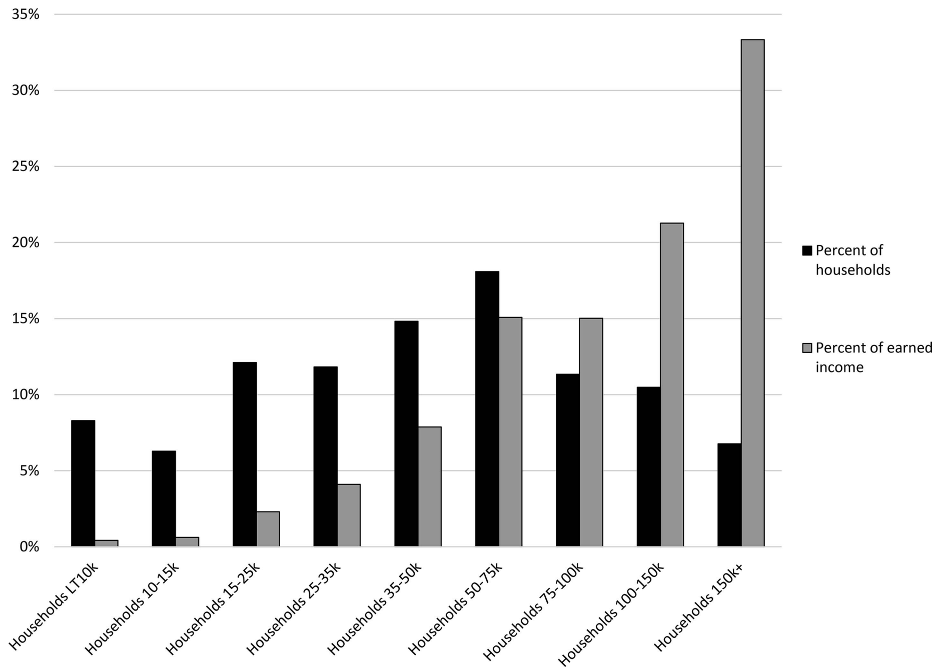

Figure 1. Comparison of the number of 2014 North Carolina households by socioeconomic class and their percentage of total model earnings.

Results and Discussion

North Carolina's 2014 population was approximately 9,944,000, with 4,396,000 residents classified as employed and receiving wages or salaries. Following the recommendation of Hughes and Shields (2007), households were chosen as the appropriate economic unit for analysis, rather than individuals, because labor force participation decisions are commonly made at the household level. The study area contained approximately 3,898,200 households, 39% of which classified as low income (less than $35,000), 44% were classified as medium income ($35,000–100,000), and 17% were classified as high income (more than $100,000). Investigation of the PUMS data, presented in Figure 1, revealed that low-income households received 7% of the total earned wages for the study area, medium-income households received 39%, and high-income households received 54% of the total wages.

The ACS respondent personal wage earnings were linked to their corresponding household's total earnings as illustrated in Table 1. Linking industry payments to households further required analyzing the PUMS data set to create unique earnings-to-household distributions for each model industry. In creating these distributions, we were given a chance to describe how indus-

Table 1. Example of how personal wages are linked to household income using the North Carolina 2014 PUMS data set.

Housing unit	Respondent household rank	Age (years)	Industry	Occupation	Personal wages	Household income	Income category
100	1	28	Sawmills/wood preservation	Industrial truck operator	$35,000	$70,000	Medium
101	1	53	Forestry	Logging worker	$28,400	$33,200	Low
102	2	36	Pulp, paper, and paperboard	Materials engineer	$67,300	$105,700	High

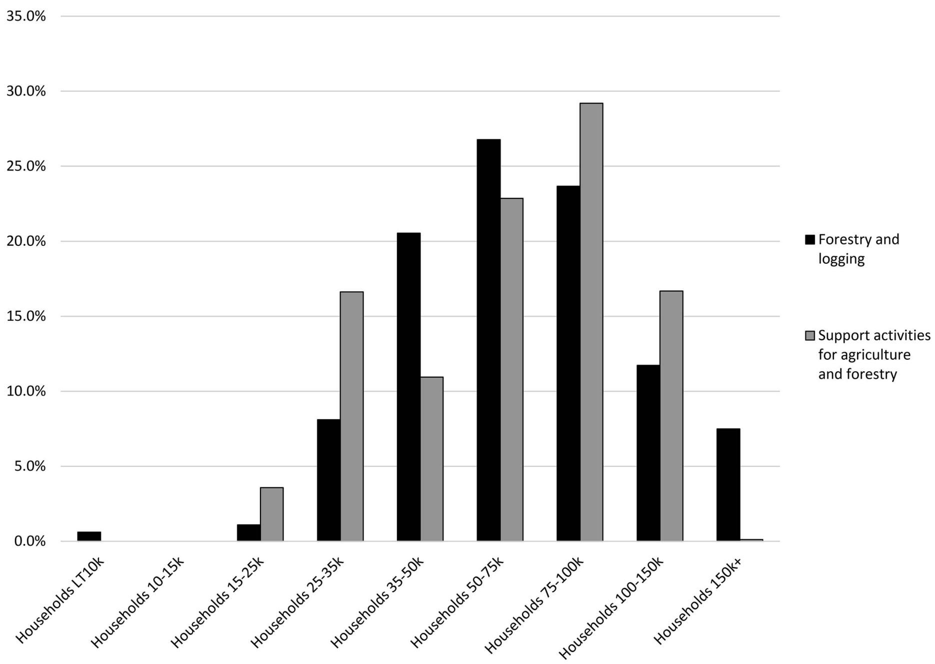

Figure 2. North Carolina 2014 industry earnings distributions for the forestry and logging and support activities for agriculture and forestry sectors.

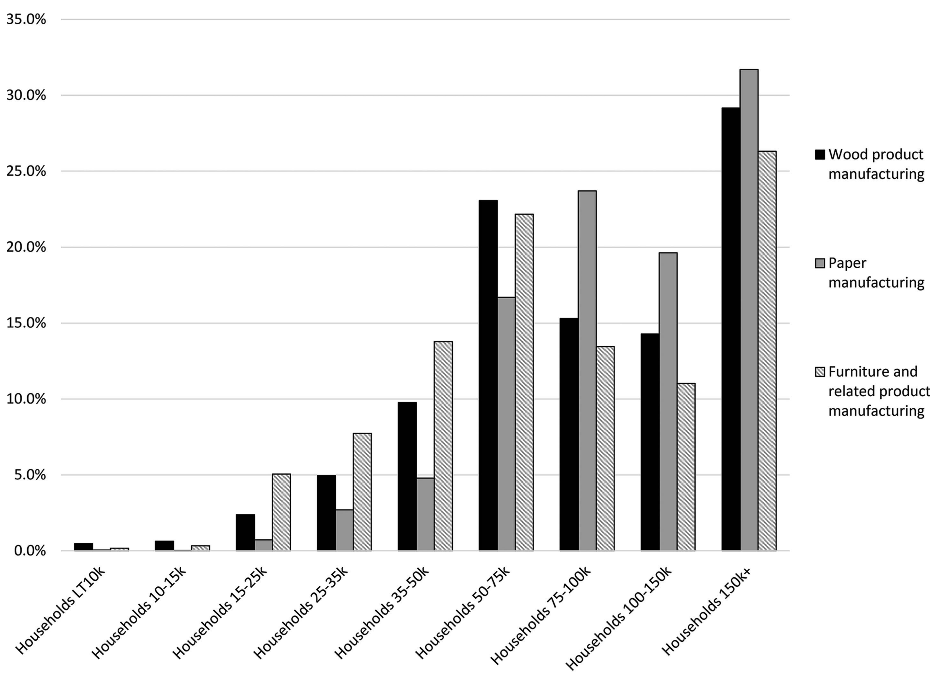

Figure 3. North Carolina 2014 industry earnings distributions for forest-based manufacturing sectors.

try wages were paid to low-, medium-, and high-income households. Forest-based and wood product manufacturing sectors were well represented within the PUMS data relative to their industry size, representing 140 and 931 household respondents, respectively. Figures 2 and 3 describe earnings distributions for North Carolina's forest product sectors and illustrate how industry wages for different sectors were distributed to stratified household income levels. These distributions, unique to each industry sector, were applied to BEA industry earnings estimates to form the *L* submatrix in our NCFOREST model. Following US Census Bureau instructions for 90% confidence intervals, forest product sector household earnings estimates varied by plus or minus 2% or less for each income category (US Census Bureau 2009).

Reviewing industry wage distributions revealed fundamentally different wage structures for forestry and logging employees compared with those working in forest products manufacturing sectors. Forestry and logging contributed more significantly to medium-income households ($35,000–100,000), with a wage distribution that was relatively symmetric across household income levels (Figure 2). On the other hand, manufacturing sectors presented a wage distribution that is highly left skewed, sending at least 25% of their earned wages to households receiving $150,000 a year or more. The difference in these wage distributions reflect the difference in skilled positions required by the two types of industries. Logging, a rural industry that requires lower-skilled and often times seasonal labor, translated its wage contributions more so to medium-income households. This structure is fundamentally different from manufacturing, which seeks to reduce low-skilled labor through automation and produce a higher unit of output per number of people employed. Jobs in manufacturing environments are likely to provide higher paid positions in the form of millwrights, electricians, maintenance, engineers, and supervisors. Thus, the manufacturing sector tends to pay wages that disproportionally contributed to higher household income.

We were able to integrate the industry wage distributions created from PUMS data within our SAM and calculated the total household earnings multipliers using the Leonteif Inverse (Miller and Blair 2009). These multipliers, presented in Table 2, describe how an increase in industrial final demand will influence the wages paid to house-

Table 2. North Carolina 2014 household earnings multipliers by socioeconomic classes.

Sector	SAM model	Low HH (<$35,000)	Mid HH ($35,000–100,000)	High HH (>$100,000)	Total
Forestry and logging (15)	NCFOREST	0.067	0.383	0.183	0.633
	Brain-dead	0.040	0.247	0.371	0.658
Support activities for agriculture and forestry (19)	NCFOREST	0.151	0.507	0.231	0.889
	Brain-dead	0.047	0.286	0.417	0.750
Wood products manufacturing (134)	NCFOREST	0.036	0.204	0.209	0.449
	Brain-dead	0.030	0.177	0.255	0.432
Paper manufacturing (143)	NCFOREST	0.019	0.144	0.174	0.337
	Brain-dead	0.023	0.134	0.168	0.325
Furniture and related product manufacturing (368)	NCFOREST	0.046	0.202	0.199	0.447
	Brain-dead	0.030	0.176	0.220	0.427

HH, households.

holds. Using forestry and logging as an example, a multiplier of 0.633 indicates that for every dollar increase in forestry final demand, $0.07, $0.38, and $0.18 cents of earnings are paid out to low-, medium-, and high-income households, respectively. The multipliers, which were different for each of the industrial sectors, created in our NCFOREST model can then be applied to specific economic scenarios to determine benefits to low-, medium-, and high-income households as a result of increased final demand.

The multipliers obtained from the NCFOREST model are different than those calculated using the traditional brain-dead method, also shown in Table 2. Comparison of the two methods offers insights into why it is more appropriate to describe earnings to households using PUMS census data rather than an aggregated regional average. Overall, differences between the total household earnings multipliers created using the two methods are relatively similar. With the exception of forestry support activities, total multipliers created using the two methods are within 5% of each other. However, the differences between our model estimates and the brain-dead method arise when assessing the distributive impacts across household income levels. In most cases, the brain-dead SAM approach underestimated the distribution of earnings to low- and medium-income households and overestimated the distribution of earnings to high-income households. It is worthwhile to note that the differences in multipliers vary depending on the industry classification.

For forestry and support activities, medium- and high-income household multipliers differed by approximately 50% from their brain-dead counterparts. These disparities are relatively smaller in forest product manufacturing sectors, where the differences ranged from 3% to 10%. Whereas earnings distributions may be closer to the brain-dead fixed income share average for forest-based manufacturing industries, forestry and support activities have earnings distributions that are much farther from the regional average. When considering the application of multipliers to hypothetical economic scenarios, conclusions drawn from using household earnings multipliers derived from a brain-dead SAM may be either accurate or poor representations based on the industry in question and how its wage structure compares to the regional average. Therefore, policies developed based on the use of these multipliers could be ineffective or even counterproductive.

Forest industries with stronger links to timber production boasted higher earnings multipliers than their manufacturing counterparts in our NCFOREST model. Forestry and its support activities household earnings multipliers were 0.633 and 0.889, respectively. In comparison, forest product manufacturing industries earnings multipliers ranged from 0.337 to 0.449. These multipliers are relatively comparable to those calculated by Arita et al. (2013), who investigated the distributive impacts of commercial fishing in Alaska. With their Alaska model, manufacturing industries produced a household earnings multiplier of 0.45. Although the authors did not disaggregate forestry from agricultural industries within their model, their agricultural multiplier was relatively high (at 1.00) compared with their manufacturing counterparts. The larger multipliers in forestry and forestry support activities found in this work can be attributed to the heavy, bulky nature of timber that tends to emphasize local production systems. These industries are labor intensive with strong supply chain linkages to local suppliers; therefore, local household spending patterns tend to experience less leakage than business spending (Hughes and Shields 2007).

Further investigation of the NCFOREST earnings multipliers indicated that low-income households do not experience the same increase in earnings as their medium- and high-income household counterparts when industry growth occurs. This is consistent with work by Marcouiller et al. (1995), who found that low-income households did not necessarily benefit from timber production because they did not own the real estate from which timber is harvested. Instead, it was more likely that low-income households benefited from forestry activity through direct employment in primary and secondary processing sectors. It was also probable that households falling into the low-income category received a significant proportion of their income from nonwage sources such as retirement, social security, and other government assistance programs. These households did not experience increases in earnings as a result of increased demand for products or services. Rather, medium- and high-income households were the main benefactors of timber production because of ownership inputs and their greater opportunities for higher-wage, skilled employment.

To understand the impacts of different multipliers in the NCFOREST model, we performed an impact analysis that assumed 10% growth in the five industries related to forest products. The assumed final demand changes for this analysis are presented alongside the base case scenario in Table 3. An overall final demand change of $2.3 billion was assumed for the state of North Carolina relative the 2014 base year. Final demand growth in these five industries generated a total economic impact of $4.16 billion. The top five nonforestry-related industries experiencing growth because of this demand change were wholesale trade; finance and insurance; real estate and rental and leasing; professional, scientific, and technical services; and health care and social assistance. Increased earnings paid to households represented 23% of the total economic impact, or $968 million. Using the NCFOREST model for the additional wages paid, low-income households received 9%, medium-income households received 46%, and high-income households received 45%.

Scenario results based on the NCFOREST model were compared alongside results gen-

Table 3. Comparison of household earnings resulting from a 10% change in final demand for North Carolina forest-based sectors.

Industry	Modeled demand change ($ million)	SAM model	$ Million		
			Low HH	Mid HH	High HH
Forestry and logging	$82.9	NCFOREST	$5.5	$31.8	$15.2
		Brain-dead	$3.3	$20.5	$30.8
		% difference	66.7	55.1	−50.6
Support activities	$86.1	NCFOREST	$13.0	$43.6	$19.9
		Brain-dead	$4.0	$24.7	$35.9
		% difference	225.0	76.5	−44.6
Wood products manufacturing	$487.7	NCFOREST	$17.5	$99.5	$102.0
		Brain-dead	$14.7	$86.3	$109.7
		% difference	19.0	15.3	−7.0
Paper manufacturing	$903.8	NCFOREST	$17.2	$130.3	$156.9
		Brain-dead	$20.8	$121.5	$151.8
		% difference	−17.3	7.2	3.4
Furniture manufacturing	$706.4	NCFOREST	$32.5	$142.4	$140.6
		Brain-dead	$21.4	$124.6	$155.6
		% difference	51.9	14.3	−9.6
All forest products industries	$2,267.0	NCFOREST	$85.7	$447.6	$434.6
		Brain-dead	$64.2	$377.6	$483.8
		% difference	33.5	18.5	−10.2

HH, households.

erated using the brain-dead model, with both scenarios assuming equal final demand changes. Total economic impact estimates for the two models were within 3% of each other, whereas estimates of total wage earnings were within 5% of one another, indicative of the multipliers' relative insensitivities even with our extensive model customization (Hotvedt et al. 1988). However, the differences between scenario results arise when the wage earnings distributions across household income levels are investigated.

As noted earlier, the NCFOREST model earnings multipliers were most different for forestry and its support activities. The brain-dead model results underestimated the wage earnings distributed to low- and medium-income households and overestimated the wages distributed to high-income households. Model disparities become important when economic development policies focus on identifying rural industry clusters in an effort to maximize benefits for communities and households on the economic margin. Strategic efforts in North Carolina have focused on developing emerging industries such as wine, handmade crafts, hosiery, and maritime-related industries using grants to support the development of community colleges, training facilities, and industrial extension education (Rosenfeld 2009). Regional policy decisions focused on increasing earnings to low- and medium-income households using a brain-dead SAM may easily overlook forestry and its support activities as relevant industries for promoting economic development in rural areas.

Model customization is also helpful when assessing the distributive impacts of forest products manufacturing industries. For furniture and other nonpaper-related forest product industries, the brain-dead SAM model overestimated earnings paid to high-income households anywhere from 7% to 10% and underestimated earnings distributed to medium-income households approximately 15%. Paper manufacturing, an industry with a wage structure more similar to the overall model average, was the one industry that experienced smaller differences between the two models. However, the brain-dead SAM still overestimated paper manufacturing's contributions to low-income households by approximately 17%.

Reviewing both industry earnings multipliers and impact analysis scenario results revealed how increases in industrial demand created increased household earnings. Confirming the results found by Leatherman and Marcouiller (1996), industrial growth in North Carolina's forest product sectors increased earnings for low-income households less so than for higher-income households. Moreover, how these industries distribute earnings to households varied considerably when augmented with industry-specific household-level data.

Therefore, taking additional steps to improve on brain-dead SAM modeling techniques is essential for policymakers interested in a relatively equitable distribution of benefits across households from all socioeconomic strata in their region or industry. Research surveys or secondary information, such as PUMS data from the US Census Bureau, can reveal the fundamentally different wage structures present within a regional economy. This research illustrates the variance found in North Carolina's forestry and forest product manufacturing industries. It is worth nothing that the PUMS data sets also provide a wealth of information regarding the roles that government payments, retirement, and investments play in contributing to household income. This information can be used to strengthen SAM research, in which information on sector structure and performance may be lacking.

Research Limitations

Traditional SAM IO modeling limitations and assumptions apply to the work contained within this study. Those not familiar with IO modeling assumptions are referred to Miller and Blair's (2009) comprehensive text on the subject or Bess and Ambargis's (2011) practical and concise summary of the technique's limitations. In addition, using the ACS PUMS data sets for characterizing industry earnings carries its own limitations. Depending on the relative size of an industry present within a study area, the number of household survey respondents can heavily vary. Not all industries may be adequately represented enough to justify the creation of an earnings distribution. In these situations, it may be appropriate to use industry aggregation. Lastly, there may be industries present within a model that are adequately described using an earnings regional average. When modeling the impacts of these industries in large study areas, use of ACS PUMS data may not be advantageous.

In addition to technical limitations with the SAM IO modeling technique, identifying quality economic impact studies is imperative. What constitutes a strong economic impact study? Meter and Goldenberg (2015) provide a helpful approach illustrated in the context of local food procurement. They point out that credible studies must clearly state assumptions upfront, recognize the role of job seasonality when reporting potential employment increases, consider product substitution alongside product price, and realistically model the response of infrastructure and distribution channels resulting from large final demand changes. When impact studies fail to communicate how these topics are addressed, practitioners should use caution when interpreting their results.

Conclusion

This work reports a method for improving on IMPLAN-based SAM modeling techniques used to investigate the contribution of industry earnings to households segmented by income. By analyzing the 2014 North Carolina ACS PUMS data set, we created industry earnings distributions unique to the study area, which described the flow of forestry and forest product industry earnings to households. In doing so, we revealed the fundamentally different earnings distributions present between forest-based industries and wood products manufacturing sectors. Household earnings multipliers derived from our augmented 2014 North Carolina SAM were different than those generated using the brain-dead SAM. Our impact analysis reflects these differences, with household earnings estimates being more than 50% different from their respective brain-dead results in some cases. These discrepancies reveal the importance of incorporating regionally specific earnings data into IMPLAN-based SAM models.

The methods described in this article can also be applied to other socioeconomic investigations because PUMS data sets provide revealing demographic and economic information. These data could be used to determine the contribution of forest-based industries to overall household income or describe the demographic of workers who make up these industries. In addition, future research investigating the role that transfer payments play in forest sector low-income households could benefit from incorporating PUMS data into their SAM models. Overall, this study emphasizes the opportunity to improve SAM models and other IO techniques by incorporating valuable secondary data.

Endnote

1. In this study earnings are defined as the sum of employee compensation and proprietor income paid by industries. The BEA refers to this as "earnings by place of work."

Literature Cited

Arita, S., M. Pan, J. Hospital, and P. Leung. 2013. The distributive economic impacts of Hawaii's commercial fishery: A SAM analysis. *Fish. Res.* 145:82–89. doi:10.1016/j.fishres.2013.02.005.

Bess, R., and Z.O. Ambargis. 2011. Input-output models for impact analysis: suggestions for practitioners using RIMS II multipliers. In *Proceedings of the 50th Southern Regional Science Association Conference*. New Orleans, LA.

Bureau of Economic Analysis. 2014. *SA5N personal income by major component and earnings by NAICS industry. North Carolina.* Available online at http://www.bea.gov; last accessed October 11, 2016.

Day, F. n.d. *Principles of impact analysis & IMPLAN applications.* Huntersville, NC: IMPLAN Group LLC.

Fleischer, A., and A. Pizam. 1997. Rural tourism in Israel. *Tourism Magagement* 18(6): 367–372.

Holland, D., and P. Wyeth. 1993. *SAM multipliers: Their decomposition, interpretation, and relationship to input-output multipliers*. Research Bulletin XB1027, College of Agricultural, and Home Economics Research Center, Washington State University, Pullman, WA. 43 p.

Hotvedt, J.E., R.L. Busby, and R.E. Jacob. 1988. Use of IMPLAN for regional input-output studies. P. 241–259 in *Proc. of the Southern Forest Economic Association.* Buena Vista, FL.

Hughes, D.W., and M. Shields. 2007. Revisiting tourism regional economic impact: Accounting for secondary household employment. *Rev. Region. Stud.* 37(2):186–206.

Hughes, D.W., and R.P. Vlosky. 2000. *Economic implications of forest products sector industry development in Northwest Louisiana.* Bulletin Number 874. Louisiana State University Agricultural Center, Baton Rouge, LA.

IMPLAN Group LLC. 2017. IMPLAN System (data and software). Huntersville, NC. Available online at www.IMPLAN.com.

Jeuck, J., and R. Bardon. 2014. *2014 income of North Carolina timber harvested and delivered to mills*. North Carolina Cooperative Extension, North Carolina State University College of Natural Resources, Raleigh, NC.

Leatherman, J.C., and D.W. Marcouiller. 1996. Income distribution characteristics of rural economic sectors: Implications for local development policy. *Growth Change* 27(4): 434–459. doi:10.111/j.1468-2257.1996.tb00976.x.

Leatherman, J.C., and D.W. Marcouiller. 1999. Moving beyond the modeling of regional economic growth: A study of how income is distributed to rural households. *Econ. Dev. Q.* 13(1):38–45. doi:10.1177/089124249901300106.

Marcouiller, D.W. 1995. The distributive economic impacts of intensive timber production. *For. Sci.* 41(1):122–139. http://www.ingentaconnect.com/content/saf/fs/1995/00000041/00000001/art00010.

Meter, K., and M.P. Goldenberg. 2015. Critical analysis of economic impact methodologies. In *Exploring economic and health impacts of local food procurement*. Illinois Public Health Institute, Chicago, IL.

Miller, R.E., and P.D. Blair. 2009. *Input-output analysis: Foundations and extensions* (2nd ed.). Cambridge University Press, New York.

Pyatt, G., and J. Round (eds.). 1985. *Social accounting matrices: A basis for planning*. The World Bank, Washingon, DC.

Rose, A., B. Stevens, and G. Davis. 1988. *Natural resource policy and income distribution*. The Johns Hopkins University Press, Maryland. 139 p.

Rosenfeld, S. 2009. *A compendium of clusters in less populated places; circumstances, interventions, and outcomes*. Regional Technology Strategies, Inc. Carrboro, NC. 120 p.

Round, J. 2003. Social accounting matrices and SAM-based multiplier analysis, in F. Bourguignon and L. A. Pereira Da Silva (eds), *The impact of economic policies on poverty and income distribution: Evaluation techniques and tools.* Oxford University Press for the World Bank, New York. p 301–320.

Sorenson, C.B., C.E. Keegan, T.A. Morgan, C.P. McIver, and M.J. Niccolucci. 2016. Employment and wage impacts of timber harvesting and processing in the United States. *J. For.* 114(4):474–482. doi:10.5849/jof.14-082.

Stone, J.R.N. 1985. The disaggregation of the household sector in national accounts, in G. Pyatt and J. Round (eds.) *Social accounting matrices: A basis for planning*. The World Bank, Washington, DC.

US Census Bureau. 2014. *North Carolina American Community Survey (ACS) 1-year Public Use Microdata Samples (PUMS)*. US Census Bureau, Washington, DC.

Van Wyk, L., M. Saayman, R. Rossouw, and A. Saayman. 2015. Regional economic impacts of events: a comparison of methods. *South African Journal of Economic and Management Sciences* 18(2):155–176.

Wagner, J. 1997. Estimating the economic impacts of tourism. *Annals of Tourism Research* 24(3):592–608.