Can Efficiency Gains in the Wood Processing Industry Conserve Forests in Developing Countries? The Case of Andhra Pradesh

Stella Z. Schons Haripriya Gudimenda Gregory S. Amacher
Kelly M. Cobourn Randolph H. Wynne Valerie A. Thomas

Abstract

Growing world demand for processed goods made from wood and a large supply of native timber in tropical regions combined with development incentives from national governments have driven rapid growth in the forest products industry in many developing countries. Contract farming schemes have emerged as an important mechanism to ensure an adequate supply of raw timber for processing. These contracts also encourage secondary forest establishment, which is argued to reduce harvesting pressure on ecologically valuable native forests. We explore whether there exists a potential for efficiency gains within the forest products industry given the current installed capacity in the state of Andhra Pradesh, India. We estimate a stochastic production frontier function for this industry based on Annual Survey of Industries data from 2010 to 2013. We present evidence that there is space for efficiency gains and that the marginal value product of wood as a raw input is high enough to justify the engagement of companies and farmers in wood supply agreements as a means to reduce pressure on native forests.

Growth in global demand for processed goods made from wood has driven rapid growth in the forest products industry in tropical developing countries, such as India. Fueled by this growth, contract farming schemes, whereby companies establish wood supply agreements with private famers and/or their representative organizations, have emerged as a potential mechanism to ensure adequate raw timber supply for the processing industry while also reducing harvesting pressure on ecologically valuable native forests (Amacher et al. 2009). As a result, the area of planted forests has considerably grown worldwide from 167.6 million hectares in 1990 to 278.0 million hectares in 2015; in India alone, the area under planted forests grew from 5.7 to 12.0 million hectares within that same period (Keenan et al. 2015). According to the Indian Paper Manufacturers Association (IPMA), 90 percent of the wood used for raw material in the country is sourced from secondary forests mostly planted and managed by the government or under contract farming schemes (IPMA 2019).

Despite investments in forest planting, the supply of raw timber in India remains inadequate to fully support the processing industry. Ghosh and Sinha (2016) argue that, as an important production factor, wood is likely to constrain the Indian forest industry's procurement of fiber for forest product supplies in the future, in part because of a high per capita rate of consumption within the country: Indian domestic consumption of wood and wood products has been estimated at 16 million tons per year, and is forecast to grow to 23.5 tons per year in a business-as-usual scenario in 2024 to 2025 (IPMA 2019). Pulp, the key raw material, forms approximately 40 percent of the raw material cost of firms and is obtained from wood, with smaller (but increasing) amounts of fiber used from waste paper and agricultural residues (IPMA 2019).

In this article, we investigate the importance of wood fiber in terms of its contribution to output value production to the forest processing industry in the state of Andhra Pradesh, India. It is in Andhra Pradesh where a large share of pulp and paper production occurs for a country that accounts for 2.6 percent of the world's paper production and which generates direct employment to 0.5 million people

The authors are, respectively, Assistant Professor, Virginia Polytechnic Inst. and State Univ., Blacksburg (szschons@vt.edu [corresponding author]; Professor, Indian Inst. of Technol. Bombay, Mumbai (haripriya@hss.iitb.ac.in); and Professor, Associate Professor, Professor, and Professor, Virginia Polytechnic Inst. and State Univ., Blacksburg (gamacher@vt.edu, kcobourn@vt.edu, wynne@vt.edu, thomasv@vt.edu). This paper was received for publication in April 2020. Article no. 20-00021.

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(Working Group on Pulp and Paper Sector 2011). Our study is based on data from the Annual Survey of Industries (ASI) conducted by the Government of India from 2010 to 2013 (ASI 2016). We estimate a production function for wood processing plants in the region that allows for inherent inefficiency by decomposing errors into those related to general stochastic shocks and those related to efficiency decreases. Inefficiency has been found to be common in production function studies of the forest industry in other countries (for non-Indian examples, see Ojo and Obalokum 2005, Gunatilake and Gopalakrishnan 2010, and Gebregziabher et al. 2012). We have found no other work that focuses on efficiency and productivity of wood processing industry in India, let alone in Andhra Pradesh.

Our analysis objectives are threefold. First, we explore the importance of wood fiber in the production processes of forest products firms in Andhra Pradesh. To do so, we identify relevant factors of production to output value level and assess the importance of raw material relative to other inputs. By computing the value marginal product (VMP) of all inputs, which represents the increase in the value of production as a unit value increase in any given input occurs, we evaluate what input is most important, that is, which input (measured in terms of value) contributes the most (on average) to the value of production for the representative forest products firm. We are then able to assess the average impact of increases in wood availability to the forest industry in Andhra Pradesh.

Second, we seek to measure the level of inefficiency of the forest products industry of Andhra Pradesh in combining raw materials to produce output, and to assess how much of that inefficiency may be attributed to raw material wood inputs. Specifically, we evaluate the relative efficiency of firms in our sample, determining where the most efficient firms are located versus where the least efficient firms reside on the theoretical production possibilities frontier. Doing so provides another key piece of information in forest conservation: more efficient firms can produce more output with a given amount of inputs or require fewer inputs to produce the same amount of output. In labor-intensive wood processing industries (often the case in developing economies), efficiency suffers by not optimizing the labor–nonlabor input mix. For example, Helvoigt and Adams (2009) have found this to be the case in a large cross-sectional study of US forest industry firms. So, we test the hypothesis that there is space for efficiency gains in the forest products industry in Andhra Pradesh.

Third, we use the results from the first two objectives above to compute the willingness to pay for wood inputs for firms in our sample. The VMP of raw wood estimated under the first objective amounts to a measure of the forest industry's willingness to pay for an increase in the supply of wood fiber.[1] A higher VMP is also indicative of greater potential pressure to remaining native forest stocks, as these are substitutes for harvesting of fiber on private planted forests in the procurement areas of the mills. Taken together with a high willingness to pay for wood fiber, the potential for efficiency gains constitutes an incentive for contract farming in the sector. We identify what firm-level inputs are important in defining the willingness to pay for raw material as well as the level of production and efficiency. Our analysis therefore speaks to the viability of agreements between firms and private farmers to supply wood in Andhra Pradesh.

The rest of the article is organized as follows. In the next section, we present an econometric model of a stochastic production frontier for the forest products firms in our sample. We estimate the econometric model and describe the methods we use for computing the VMP of raw material wood inputs as well as for measuring inefficiencies among firms. In the third section, we discuss our empirical data from Andhra Pradesh and present estimation results. The final section presents conclusions and policy recommendations.

Econometric Model

In this section, we present a stochastic production possibilities frontier model for the forest products industry in Andhra Pradesh that addresses the three overall objectives of our study discussed earlier. From the stochastic frontier model, we estimate production functions for forest products firms assuming efficiency is not simply 100 percent across firms in our sample and then we derive the VMPs for each productive input. However, first we present a forest products production technology model describing the relationship between inputs and output. We model a wood processing firm that produces pulp and/or paper and that fits our empirical data. Wood is a main input into production and, along with other inputs, determines the value of output for firms in the sample region.

The relationship between input use and output for each firm can be described with the stochastic production function:

$$y_i = f_i(T_F, \psi_F, S, \varepsilon_i; \beta) \quad (1)$$

where y_i is tons of paper produced by firm i, or equivalently, the value of this output obtained by multiplying tons of paper by its market price, which all firms take as given;[2] T_F is a vector of non–raw material inputs, such as labor and fuel, for firm i; ψ_F is vector of raw material inputs, mainly wood fiber in this study; S is a vector of other characteristics that can affect production, such as technology level or firm size (proxied by fixed capital investments) and value of working capital, which is a measure of liquidity and may serve as a proxy for financial health and, thus, managerial quality;[3] and ε_i is a stochastic error term that reflects shocks

[1] The maximum stumpage price the processor will pay to a farmer for harvesting at the farm site is therefore the VMP less any transportation costs paid to move the harvested material to the mill. The efficiency of forest processing firms impacts this VMP and therefore maximum willingness to pay. Less efficient firms require more inputs for a given output, or conversely, produce less output for a given set of wood raw material. Thus, as firms become more efficient, their willingness to pay for wood increases, and we would expect more situations where willingness to pay is higher than the costs farmers incur to devote land units to forest production.

[2] Value of output and output levels are identical for the purposes of estimation of Equation 1 given that firms are price takers in the wood markets that we examine; there are numerous firms and farmers growing trees and all firms produce what we assume to be a virtually identical, that is, homogenous product – for example, paper.

[3] Other variables that may be included within vector S and that were available to us are whether the firm is ISO certified or not, whether they were public or private, and whether they were located in a rural versus an urban area. However, none of these variables were relevant in the estimation of our model.

to a firm's production that are not observed by the researcher, e.g., managerial skill, regional political conditions, weather that affects harvesting, and the condition or location of local resource stocks. The term β is a vector of coefficients to be estimated for the explanatory variables present in vectors T_F, ψ_F, and S.

Using Equation 1, we can estimate the value of forest plantations to production as the VMP of wood, a main raw material input in the production of pulp and paper. The VMP is defined as the additional value of production that one additional unit of raw material affords, holding constant all other factors of production. Equation 2 defines the VMP for firm i in our sample:

$$VMP_i = p_F \frac{\partial \widehat{y_i}}{\partial \psi_F} = \frac{df_i(T_F, \psi_F, S; \hat{\beta})}{d\psi_F} \tag{2}$$

where p_F is the exogenous price of the forest product, $\widehat{y_i}$ is the *estimated* quantity of paper produced for firm i from Equation 1, and $\hat{\beta}$ is the vector of *estimated* coefficients from Equation 1.

The left-hand side of Equation 2 is also interpretable as firm i's maximum willingness to pay for one more ton of raw material wood. This is, in fact, one important indicator of the value of establishing contract agreements for supplying wood from planted forests: what a firm would pay for wood on any farmer's land is the VMP less the costs for the firm to transport and process the wood.

A critical aspect in the estimated VMP for wood processing firms is the technical efficiency with which firms combine inputs in order to generate output. The production function in Equation 1 implicitly assumes that firm i is 100 percent efficient, which means that there is no technical inefficiency (e.g., waste) in its ability to combine inputs to produce paper outputs. Inefficiency implies that greater wood procurement is needed to achieve a given output of forest products.

The economics literature has established that a reasonable assumption is that forest processing firms in any random sample within a developing country will vary in achieving efficiency and will likely exhibit noticeable inefficiencies; this has been found by Gunatilake and Gopalakrishnan (2010) and Ojo and Obalokun (2005), but has also been shown in paper industries in developed countries (Grebner and Amacher 2000, Helvoigt and Adams 2009). Differences in inefficiencies of production across firms are expected reflecting unobserved differences in managerial skills and experience, unknown shocks in both input and output markets, and weather shocks that render input choices made before the shocks incorrect. There are also likely differences in the quality of inputs (such as wood quality)[4] that are not observed by the researcher and probably not known when firms make decisions about input use in Equation 1.

Regardless of the reasons, more-inefficient firms will be observed having either lower output or lower VMP given a certain level of inputs. Conversely, these firms will require more inputs to produce the same output as a more efficient firm. We accommodate this feature of production by estimating Equation 1 using a stochastic frontier production function (Kumbhakar 1990):

$$y_i = \gamma_i f_i(T_F, \psi_F, S, \varepsilon_i; \beta) \tag{3}$$

Where ε_i is an error term in the estimation of Equation 3, and $\gamma_i \in [0,1]$ is an unobserved inefficiency shock that is firm-specific and reduces the value of production for firm i. A value for γ_i closer to zero is consistent with greater inefficiency for firm i, while a value equal to one implies there is no inefficiency in production. The econometric interpretation of γ_i is that it accounts for reductions in output of a given firm relative to the frontier of maximum output that is achieved by the most efficient firms in the sample. This parameter is not the same as the error ε_i, which accounts for unobserved changes in output that may or may not affect all firms equally. An example of such an error would be power outages or worker strikes.

In the development economics literature, much of the progress in understanding the econometric application of stochastic frontier production functions has come from studying inefficiencies within subsistence household agriculture (Battese 1992, Seyoum et al. 1998, Mochebelele and Winter-Nelson 2000, Binam et al. 2004, Gebregziabher et al. 2012). Following this literature, an estimable form of Equation 3 is derived by the decomposition of the error term ε_i to separate unobserved technical inefficiency shocks that affect skewness of residuals from unobserved, mean-zero stochastic random shocks. This decomposition is achieved by rewriting the production function as $y_i = f_i(T_F, \psi_F, S; \beta)\exp(v_i)\gamma_i$, where now $\varepsilon_i = \exp(v_i) \cdot \gamma_i$ and the term $f_i(T_F, \psi_F, S; \beta)$ is interpreted as a deterministic frontier that is industry specific and production-technology based. Firms producing below this frontier are productively inefficient with $\gamma_i < 1$ for a given set of inputs. Term v_i is a pure stochastic error shock and is composed of unobserved factors and measurement errors in production, separate from inefficiency shocks.

Taking logs of both sides of the transformed production frontier we have:

$$\ln y_i = \ln f_i(T_F, \psi_F, S; \beta) + v_i - u_i \tag{4}$$

In Equation 4, the log transformed error term now has two separate components, $\varepsilon_i = v_i - u_i$, one of which is the monotonically transformed efficiency shock, defined as $u_i = -\ln \gamma_i$. At best, a firm can be exactly on the frontier, so that $0 \leq \gamma_i \leq 1$; as a result, the error is one sided, that is $u_i \geq 0$. In Equation 4, the VMP for each input is simply the corresponding estimated coefficient (that is, the corresponding element of β), given the form of the specification. There are three distributional assumptions commonly used in the literature when estimating u_i in Equation 4: half-normal $N^+(0, \sigma_u^2)$, truncated normal $N^+(\mu, \sigma_u^2)$, or exponential $\exp(\lambda)$. In the results below, the half-normal distribution best fits the data and all fit tests show it to be the valid specification for Equation 4. In all cases, the error component, v_i, is stochastic and follows a standard normal distribution $N(0, \sigma_v^2)$.

Once the stochastic frontier is estimated, firm-specific efficiency scores, measured by the distance of the firm's production from the theoretically best frontier (with $\gamma_i = 1$), are calculated in the following way:

$$\gamma_i = \frac{f_i(T_F, \psi_F, S; \hat{\beta})e^{v_i - u_i}}{f_i(T_F, \psi_F, S; \hat{\beta})e^{v_i}} = e^{-u_i} \tag{5}$$

[4] Although we recognize that wood quality may affect output quality and cost, we do not have information on the quality of raw materials which firms in our sample work with.

In Equation 5, $\hat{\beta}$ is the estimated coefficient vector from the regression in Equation 4. Although Equation 5 as written is unobserved because of the error components, it can be predicted using the conditional expectation $E(e^{-u_i}|\varepsilon_i)$ (Jondrow et al. 1982; Battese and Coelli 1988, 1995; Kumbhakar 1990).

To fully characterize Equations 4 and 5, the parameter vector $\hat{\beta}$ in Equation 5 is estimated simultaneously with other model parameters in Equation 4 using a one-step maximum likelihood approach. The likelihood function for the assumed half-normal specification in vector form (for all i firms) is defined as follows:

$$\ln L = \sum_{i=1}^{N} \left(-\frac{1}{2}\ln[2\pi] - \ln \sigma_T - \ln \Phi\left[\frac{\mu}{\sigma_u}\right] + \ln \Phi\left[\frac{\mu}{\sigma_T d} - \frac{\varepsilon_i d}{\sigma_T}\right] - \frac{1}{2}\left[\frac{\varepsilon_i + \mu}{\sigma_T}\right] \right) \tag{6}$$

where $\mu = \beta' z_i$, $d = \sigma_u / \sigma_v$, $\sigma_u = d\sigma_T / \sqrt{1+\lambda^2}$, $\sigma_T = \sqrt{\sigma_u^2 + \sigma_v^2}$. When $\mu = 0$, the above specification is the same as the half-normal efficiency model $N^+(0, \sigma_u^2)$ (for more details, see ''sf model'' command in Kumbhakar and Lovell 2003).

Data and Econometric Results

To simultaneously estimate Equations 4 and 5, we extracted the data on forest processing firms located in Andhra Pradesh from India's ASI (2016). The survey is an annual census that includes formal manufacturing units for all industries across Indian states, covering the firms registered under the country's Factories Act (Kathuria et al. 2013). Our dataset includes information on the inputs and outputs relevant to forest processing mills in Andhra Pradesh for years 2010 to 2013, yielding 638 observations. We excluded from the analysis observations for which data were missing in terms of explanatory variables. To accommodate the fact that the years of available data are not uniform across mills, and taking into account that the inflation rate has changed minimally over the time covered in the sample, we treat different years as separate observations in a stacked fashion. Explanatory variables available for each mill include firm type, location, and inputs and output measured in value terms (Indian rupees [Rs]). The majority of these mills produce pulp and/or paper, and all use wood harvested from planted forests as their primary raw material input.

Descriptive statistics are presented in Table 1. Roughly half of firms are government owned and half are privately owned. Given that ownership may affect inefficiencies, a dummy variable for ownership was included in the estimation of Equations 4 and 5. The majority of firms are also now environmentally certified (using the International Organization for Standardization 14001 standard [ISO 2015]), and half are located within an urban area. The urban–rural distinction could be important due to access to labor, although in many cases, laborers live in and around the mills in which they work. Often in Indian forest products firms, laborers have their lodging paid through emoluments, which were common in the data.

Table 2 presents descriptive statistics for inputs to production measured in rupees (1 Rs = US$0.015). Although most variables are self-explanatory, we mention a few that have definitions specific to the ASI database: ''gross value of output'' is defined as the total sum of ex-factory value of products and products produced by the firm during the accounting year, ''labor'' is defined as the addition of both production line workers as well as other supporting employees and is measured as the total number of persons engaged in the production activity during the year, and ''invested capital'' is defined as the value of gross fixed assets engaged in the industry.

Referring to the results in Table 2, we find that mills in our sample region are quite large, with a labor force of over 450 people per unit, and an average value of production equal to over 704 million Rs (approximately US$10 million) per year. The average total value of inputs is 48.9 percent of average gross value of outputs and total cost of production is 55.7 percent of gross value of outputs, indicating that the average mill in our sample is profitable even if not perfectly efficient. Considering the input shares in relation to output values, we find that raw materials, that is, wood, is highest (26.3% of the value of output), followed by fuel (11.3%) and labor (8.9%). Despite the fact that the labor input share is the lowest of the types of inputs considered, industrial production is predominantly labor intensive in India and it is likely to involve inefficiencies due to lack of automation (Rao 2017) and/or simply due to overemployment of labor relative to capital given low wage values (Krugman 1991). The higher share of raw materials in relation to total output is expected as it is the main material input that is transformed into pulp and paper and their cost is high (Rao 2017). Raw materials are, however, expected to be a

Table 1.—Descriptive statistics for Annual Survey of Industries firm data.

Categorical variable	Observations (n)[a]	Observations (%)
Rural location	638	51.17
Urban location	638	48.36
Privately owned	463	42.76
Individual proprietorship	463	17.71
Government owned	463	57.24
Not ISO 14001 certified[b]	127	91.34
ISO 14001 certified	127	8.66

[a] Refers to number of firms for which data are not missing.
[b] ISO 14001 refers to a series of environmental responsibility standards as defined by the International Standard Organization (ISO 2015).

Table 2.—Descriptive statistics for production inputs and outputs measured in rupees (Rs).

Variable	Observations (n)	Mean (SD)
Invested capital (million Rs)	406	103.00 (513.00)
Gross value of fixed capital (million Rs)	406	1,050.00 (3,590.00)
Value of working capital (million Rs)	452	94.50 (432.00)
No. of workers	420	207.08 (547.20)
Total value of wages (million Rs)	420	22.00 (59.40)
No. of employees	454	359.35 (871.25)
Total value of salaries (million Rs)	454	41.30 (113.00)
Value of materials (million Rs)	421	185.00 (523.00)
Value of fuel (million Rs)	459	79.70 (214.00)
Total value of inputs (million Rs)	459	344.00 (991.00)
Total cost of production (million Rs)	641	392.00 (1,480.00)
Gross value of outputs (million Rs)	372	704.00 (2,220.00)

constrained factor of production because raw materials must be harvested mainly from private lands and outside of natural forests (Vanam 2019).

We now turn to econometric estimation of Equations 4 and 5 for our sample of forest products firms. Missing data reduces our estimable model to 187 observations. Table 3 presents the estimation results for Equation 4. A note must be made before we move forward with the presentation of the results: Because of the restriction on harvesting timber from natural forests imposed by the National Forest Policy of 1988 (Vanam 2019) and because ninety percent of the industrial wood comes from secondary public and private forests (IPMA 2019), we believe it is safe to assume homogeneity in the quality of raw materials. The VMP associated with the homogeneity assumption is conservative, that is, lower than if the quality of raw material were observable (eventual unobserved differences in quality are absorbed in the error term).

The dependent variable is the log of the value of production in rupees. All inputs are in log form, consistent with Cobb-Douglas technology common in the literature (unless otherwise noted or a dummy variable). The regression is highly significant with a Wald statistic significant at the better than 1 percent level, as are the tests for significance of the error shocks, all of which are significant at higher than 1 percent significance levels. The error tests indicate that there is significant inefficiency in the data for firms in our sample; therefore, the stochastic frontier model is the correct specification. In fact, both the efficiency and the stochastic error terms are significant at better than 1 percent levels. The efficiency-based error is slightly more important than the pure stochastic disturbance error, with an estimated residual value of 0.086 for the inefficiency-based error versus 0.053 for the pure stochastic error, although they are close enough to be judged equally important to unobserved changes in forest product output.

Based on the estimated coefficients for the explanatory variables, all factors of production have positive and significant effects on output. This is expected as an increase in inputs yields an increase in outputs, even if a firm is not 100 percent efficient. The variables that are most significant in determining output are fuel and raw materials, both of which are significant at lower than the 1 percent level. The least important input (though still positive and significant at the 1% level) is labor. These results are consistent with our discussion of descriptive statistics in Table 2. That is, fuel and raw materials are likely the most constraining inputs.

Because we use a Cobb-Douglas production function specification, the estimated coefficients in Table 3 are equivalent to the estimated VMP, as per Equation 2. Our results indicate that raw material has a VMP approximately five times higher than the other inputs in the production function; in fact, each additional rupee of this input used in production results in an increase of 0.6 $Rs in terms of the value of production. This is indicative of the potential pressure the forest industry puts on forest stocks and shows that improving incentives to establish trees on farms through contract farming within mill procurement regions could be important to reducing pressures on native forests.

The VMP of raw material is also an indicator in the stochastic frontier model that this input is likely central to efficiency; nonlabor inputs have frequently been found to be critical to technical inefficiency in wood processing industry frontier models such as ours (see, for example, Helvoight and Adams 2009). Given the high VMP that we find, the forest products sector may be willing to pay for the establishment of planted forests, which should be a driving factor in the development of wood supply contracts in the region between farmers and the industry.

The estimated efficiency scores as per Equation 5 (and derived using the estimated coefficients from Table 3) are presented in Table 4. These results show the extent of inefficiency and, most importantly, the distribution of efficiency levels across firms. We find that the most efficient forest product firms in Andhra Pradesh are within 95 percent of the theoretical production frontier, while the most inefficient firms are within 33 percent of this frontier. It is possible that labor is overemployed or that there is a relative scarcity of the raw material input, as would be the case if firms in our sample must purchase wood from distant yards. Indeed, Gunatilake and Gopalakrishnan (2010) found inefficiency resulted from the relative scarcity of inputs in their sample of sawmills in Sri Lanka, whereas Ojo and Obalokun (2005) found proximity to government forests and availability of wood to be predictive of inefficiency for wood processors in Nigeria.

To examine the pattern of inefficiencies further, a histogram showing the distribution of efficiency for firms in the sample relative to the (theoretically best) frontier is in Figure 1. Most of the firms are within 75 to 85 percent of the

Table 3.—Stochastic frontier estimates (Eq. 4).[a,b,c]

	Coefficient	SE	z	P > z	95% CI
Independent variables					
ln(value of fuel)	0.118	0.023	5.17	0.000	0.073–0.163
ln(value of materials)	0.622	0.036	17.13	0.000	0.550–0.693
ln(total value of salaries)	0.114	0.039	2.93	0.003	0.038–0.190
ln(value of working capital)	0.074	0.020	3.78	0.000	0.036–0.112
ln(gross value of fixed capital)	0.116	0.035	3.27	0.001	0.046–0.185
Constant	0.727	0.249	2.92	0.004	0.239–1.216
	Coefficient	SE	t	P > t	95% CI
Error terms					
sigma_u_sqr	0.086	0.030	2.82	0.005	0.043–0.172
sigma_v_sqr	0.053	0.011	4.99	0.000	0.036–0.078

[a] The value marginal product for each input is equal to the coefficient estimate.

[b] Log likelihood –32.241898; no. of observations 187; Wald $\chi^2(5) = 11133.680$; prob $> \chi^2 = 0.000$; likelihood ratio test = 6.3456.

[c] Dependent variable = ln(gross value of outputs).

Table 4.—Estimated efficiency scores (Eq. 5).

Efficiency scores measure	Observations (n)	Mean (SD)	Min	Max
Proportion of maximum output at the which the firm is operating (technical efficiency)	187	0.8075 (0.0782)	0.3326	0.9536
Proportion of output lost due to technical inefficiency	187	0.2289 (0.1221)	0.0485	1.1172

frontier, with 17 operating within 82 percent of the frontier. Given the importance we find for the raw material input in the VMP estimation and the results in Table 3, there is evidence of space available for increased efficiency in the forest products industry in Andhra Pradesh, representing a potential opportunity for further establishment of planted forests, and for firm–famer contract agreements or contract farming.

Conclusions and Policy Implications

In this analysis, we used industry census data from 2010 to 2013 for the state of Andhra Pradesh, India, to investigate the importance of raw material inputs to the output of the state's forest products sector. We assess the technical inefficiencies exhibited by these firms and the importance to efficiency of raw material inputs to production (wood and fiber based). Our overriding goal was to understand the importance of raw materials to the forest industry in the Andhra Pradesh region, as a first step to assessing both future pressures on native forests and the incentives facing the industry to work with farmers in establishing forest plantations through contract farming. A precursor to answering these questions is computing the value of raw material to forest products output to determine the forest industry's theoretical willingness to pay for wood. This value depends on firms' efficiency in combining inputs to produce wood-based outputs.

We employ a stochastic frontier production function approach that allows for the possibility of both inefficiency in production and random shocks that are unobserved in firm-level data. We find that raw materials have a key role to play in improving efficiencies, and in generating a firm-driven willingness to pay for wood fiber from farmers in Andhra Pradesh. Firms in our sample are quite labor intensive in the production of wood products, with an average of 452 employees per firm. Their largest component of variable costs is raw material inputs, followed by fuel and labor. Despite presenting the highest input to output value share (26.3%), raw wood is a constraining factor in production. Mills in the sample are profitable, with an average total cost of production per firm in the sample corresponding to 55.7 percent of gross value of outputs.

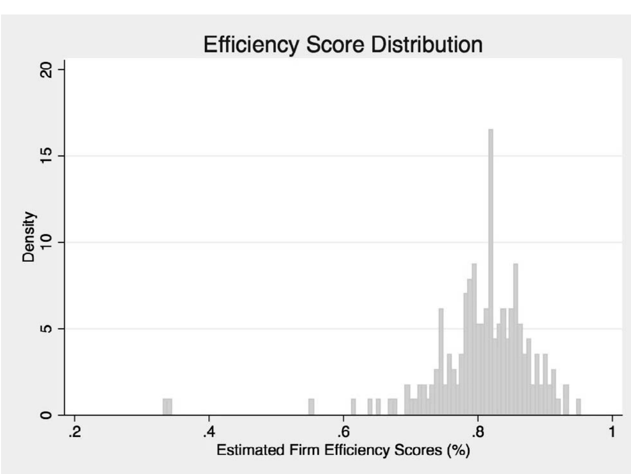

Figure 1.—Histogram of estimated efficiency scores by firm in the sample.

We find evidence of significant inefficiencies in our sample, with the least efficient firms producing approximately 33 percent inside the frontier. The variables most significant in driving differences in efficiency are raw materials and fuel. Moreover, our analysis reveals a value of marginal product of raw materials that is approximately five times higher than that of labor and fuel. This implies that the addition of any given value of the raw material input increases production value by 62 percent of that input value. Our results thus indicate that the forest industry in Andhra Pradesh could benefit from greater raw wood availability.

Given procurement regions and transportation costs, greater wood availability could come from agreements with farmers to establish forest plantations. The forest industry would be willing to pay for such agreements (perhaps in terms of seedling sharing and technical assistance), according to our results. From the government's perspective, if a goal is to protect remaining native forests, then taken collectively, our results suggest that the government should seek to foster these relationships. Doing so could not only improve efficiency of the forest industry, but could perhaps open up additional opportunities within the region such as carbon market access that could increase rents to growing trees on agricultural lands, further protecting native forests and improving forest industry efficiency. The fact that the forest industry has already begun to establish nurseries for seedlings is an indication that the private sector realizes these opportunities. Although such nurseries are still in the early stages of development and at a scale too small for proper econometric analyses, understanding their importance as we have done here is a critical first step in improving welfare within the region. Specific study of these nurseries remains an important topic for future research as the region continues to transition.

There is some hope that raw material constraints on the wood-based industry could be lessened through policies recently proposed. For example, the revised 2018 draft of the new National Forest Policy in India includes a proposal to mitigate climate change through sustainable forest management and encourages ''public–private participation models'' for undertaking afforestation and reforestation activities in degraded forest areas and the forest areas available with ''Forest development corporations and outside forests'' (Ministry of Environment, Forest and Climate Change 2018). The Indian pulp and paper industry would be one of the prime beneficiaries of these new policies.

Our results also suggest that policies supporting public–private participation models could create an incentive for the industry to enter into agreements with farmers to grow trees on their lands in contract farming arrangements that are already common in the agriculture sector in India. The private relationships developed through wood industry investment in farmer plantation establishment is a very different policy outcome than the historical approach to forest management in India and in much of the developing world, in which public and nongovernmental organization investments are made in forest plantations through social forestry projects in order to ensure stable sources of fuelwood for surrounding villages. Our efficiency findings and the important contribution of raw material inputs to value of production suggest, however, that this may also need to be considered if the ultimate goal is to ensure stable forest cover and public goods production from forests, besides employment and economic growth.

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