Estimating Price and Income Elasticities of Demand for Forest Products: Cluster Analysis Used as a Tool in Grouping

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Abstract

Well-estimated elasticities of demand are important for making long-run projections in demand for forest products. In this research, cluster analysis is used to group 180 countries contained within the Global Forest Products Model (GFPM), using cross-sectional data for per capita gross domestic product (GDP), forest coverage, and per capita consumption of forest products, for forest products including plywood, particleboard, fiberboard, newsprint, printing and writing paper, and other paper and paperboard. The application of cluster analysis prior to estimating the elasticities of demand solves the problem of data availability in estimating elasticities by grouping countries based on variables identified from economics theory and enabling the extension of elasticity estimates to countries that are similar to others in a cluster, but without data for directly estimating elasticties. Mean absolute deviation is used for data standardization, and the k-medoids approach and silhouette technique are used in cluster analysis. Statistics of clusters for every forest product show various combinations of countries with similar levels of per capita GDP, forest coverage, and consumption, such as a cluster with high per capita GDP,

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low forest coverage, and high consumption of the discussed forest product. The results of the cluster analysis are validated by a one-way analysis of means and multiple comparisons. Countries for panel analysis are selected based on time series data availability and quality. As implied by cluster analysis, some of the countries in the cluster can be used to represent the whole cluster. In this research, long-run static models, short-run dynamic models, and long-run dynamic models of demand are estimated using panel data analysis for countries in each cluster using data from 1992 to 2007 and 9 to 44 countries in each cluster. We found that long-run dynamic elasticities are higher than short-run dynamic estimations, and dynamic model estimations outperform static model estimations as shown in RMSE statistics.

Keywords: cluster analysis, elasticity of demand, static model, dynamic model, forest products

1. Introduction

Well-estimated price and income elasticities of demand are important for understanding consumer behavior and for making long-run projections in global and national demand for forest products. Estimating elasticities of demand for forest products has been the topic of much research. Buongiorno (1978, 1979), using panel data of 43 high- and low-income countries, estimated price and income elasticities of demand for newsprint, printing and writing paper, other paper and paperboard, coniferous sawnwood, nonconiferous sawnwood, plywood, particleboard, and fiberboard. Simangunsong and Buongiorno (2001) estimated price and income elasticities of demand for nine end-use forest products using panel data analysis from 64 countries, also divided into high and low income.

The Global Forest Products Model (GFPM, Buongiorno et al., 2003), examines 180 countries and 14 forest products, and provides an efficient and flexible tool for the analysis and long-run projections of forest product price, demand, supply and trade on a global, regional and national basis (Zhu et al., 1998; Zhu and Buongiorno, 1999; Trømborg et al., 2000). Several other researchers, including Brooks (1995) and Chas-Amil and Buongiorno (2000), have performed analyses of the long-run elasticity of demand for forest products although only looking at a limited number of countries. Turner and Buongiorno (2004) estimated the elasticities of demand for imports of forest products for 64 countries.

The aim of this research is to estimate price and income elasticities of demand for forest products among various groupings of countries. The research consists of two stages. In the first stage, the 180 countries included in the GFPM are grouped into clusters using cluster analysis. In the second stage, elasticities of demand for forest products are estimated utilizing a panel data analysis of each cluster.

Cluster analysis is described as "the art of finding groups in data" (Kaufman and Rousseeuw, 1990, p. 1) and has been used by biologists and social scientists for over half of a century (Kaufman and Rousseeuw, 1987). Cluster analysis is also used in forest science (Atta-Boateng and Moser, 1998; Yeha et al., 2000). For example, Roos et al. (2001) analyzed differences in Swedish sawmill production strategies using cluster analysis. Previous research applying cluster analysis with panel data analysis to estimate international elasticities of demand for forest products has, however, not been found.

Cluster analysis is implemented before estimating elasticities of demand for forest products in this research for several reasons. First, it is time-consuming to undertake an elasticity of demand analysis for every country and every forest product, considering that 180 countries and 14 forest products are used in the GFPM. Second, there are no available time series data in some countries, and sometimes, the same data are reported for continuous years, so one cannot reliably estimate elasticities of demand for these countries. Third, while some estimates of demand elasticities group countries, the criterion for the grouping is ad hoc. For example, Kallio et al. (1987), dealing with 18 countries and regions, estimated four groups of demand elasticities in the GTM model by level of income per capita＞ US$3,000, US$1,500 – US$3,000, US$750 – US$1,500, <US$750 per year, for nine forest products. Tachibana et al. (2005) grouped countries into developed countries, medium-developed countries and developing countries to estimate the elasticities of demand.

Cluster analysis seeks to group countries into clusters based on their similarities across a number of variables. Therefore, the results of estimations for a cluster using panel data analysis on some countries within the cluster could be extended to all the member countries, which can solve the problem of data availability and increase efficiency in estimating global elasticities.

This paper deals with 6 end-use forest products: veneer and plywood, particleboard, fiberboard, newsprint, printing and writing paper, and other paper and paperboard. Among the nine end-use forest products dealt with in GFPM, fuelwood and charcoal, and other industrial roundwood are not taken into account due to their data unavailability and sawnwood has been discussed in a previous paper (Michinaka et al., 2010).

2. Cluster Analysis

2.1 Data

The three variables, per capita gross domestic product (GDP), forest coverage, and per capita consumption of the corresponding forest product, are used in the cluster analysis to group countries for estimating the elasticity of demand for forest products. Economic theory tells us that the demand for inputs to production is decided by own price, prices of related inputs, output production, techniques of production, producers' preferences, expected future prices, etc. (Varian, 1992; Samuelson and Nordhaus, 2001; Fischer et al., 1988). Forest coverage, i.e., the percentage of forest area in land area, where forest area is defined as "the land spanning more than 0.5 hectares with trees higher than 5 metres and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ" in FAO (2011), is included in the analysis because countries covered by dense forests tend to consume more forest products (reflecting producers' tastes or preferences), and some governments, like in Japan (Japan Forestry Agency, 2009), often implement policies to encourage utilization of forest products. Per capita consumption level is included because the definition of elasticity of demand indicates that one can find that current consumption level, at the point where elasticity is to be calculated, is a factor that affects demand elasticities (Varian, 1992, p. 235).

Per capita GDP statistics, in 2005 U.S. dollars, are from the World Bank (2009). Forest coverage data in percentage points are from the FRA 2005 (FAO, 2009), which defines forest coverage as . Per capita apparent consumption is sourced from FAO (2009). Because per capita consumption is minimal in numerous countries, consumption per 1,000 persons is used. To smooth fluctuations in the cross-sectional data used in the cluster analysis, three-year average data from 2005 to 2007 are used.

Data used in the cluster analysis were standardized for two reasons. Firstly, using different units of measure for the same variable in the cluster analysis will lead to different country groupings. For example, the per capita consumption of newspaper can be expressed in kilograms or in tonnes, but the results will be different when using kilogram compared with using tonne. This is because the use of different units of measure will lead to data sets with different means and variances. Secondly, data standardizing allows variables to contribute equally because different variables have different means and variances. Standardizing converts the original data to unitless variables.

The most commonly used standardizing function is z-scores:

$$Z_{ij} = \frac{X_{ij} - \bar{X}_i}{S_i},$$

where X_{ij} is the original data, $\bar{X}_i$ is the mean for the *i*th variable, and S_i is the standard deviation for the *i*th variable. In the partitioning around medoids approach, described in the next section, the mean absolute deviation is used instead of the standard deviation to disperse the impacts of outliers.

2.2 Cluster analysis approaches and determination of the number of clusters

The partitioning around medoids (PAM) or k-medoids method, one of the nonhierarchical approaches to cluster analysis, developed by Kaufmann and Rousseeuw (1987), finds k clusters with k representative objects in the data, trying to assign each object of the data set to the nearest representative object. Compared with the k-means method, which aims to partition n objects into k clusters in which each object belongs to the cluster with the nearest mean (centroid), PAM is robust to noise and outliers, because the centroid is easily affected by outliers while the medoid is not. Finally, under PAM, a silhouette statistic shows how well an object lies within the cluster, and silhouette plots and averages are powerful tools for determining the number of clusters in data.

Determining the number of clusters is an important step in cluster analysis. Three methods are considered in determining the number of clusters used in this research. The first is the rule of thumb (Mardia et al., 1979, p. 365), $k = \sqrt{n/2}$. The results from this approach are taken only as a reference because this approach cannot give strictly accurate, reliable, and integer results. The second is the stopping or elbow rule, in which the number of clusters is determined at the elbow point of the within-group sum of squares (WGSS) curve. Plots of the WGSS can show the range where the elbow point is located and can be a reference in deciding the number of clusters. The third approach, the most important in this research, is the silhouette statistic, where the number of clusters is determined as that which maximizes the silhouette width. Often the silhouette width is maximized when clustering all the discussed countries into two groups. As we would like to take the diversity of the selected countries into account, the global maximization is abandoned, and a local maximization, or the second best, is adopted, while referring to the results from other two approaches (Michinaka et al., 2010).

2.3 Results

As the nature of demand for different forest products varies across countries, cluster analysis is undertaken for each forest product. Because we would like to use the results of our analysis in the GFPM, we use the 180 countries in that model as our object. Table 1 shows the countries and their codes (Zhu et al., 2009). Tables 2 through 7 show the results of the cluster analysis for plywood (118 countries), particleboard (93 countries), fiberboard (111 countries), newsprint (105 countries), printing and writing paper (122 countries), and other paper and paperboard (127 countries). Some countries are not included in the cluster analysis because of incomplete data. Those countries that are included in the estimation of demand elasticities in the next stage are shown in bold and italic letters. Countries with the same data reported over 4 years, or with more than 4 years of missing data, or negative apparent consumption, are deleted in the panel data analysis.

Table 1 Region names and their codes

Table 2 Results of cluster analysis for plywood

Table 3 Results of cluster analysis for particleboard

Table 4 Results of cluster analysis for fiberboard

Table 5 Results of cluster analysis for newsprint

Table 6 Results of cluster analysis for printing and writing paper

Table 7 Results of cluster analysis for other paper and paperboard

2.4 Tests for cluster analysis results

One-way analysis of means (not assuming equal variances) is used to test if clusters differed significantly in the means for all of their three variables. The null hypothesis is that the samples in all groups are drawn from the same population. The results show that not all the clusters have the same means, or some cluster(s) have different means than other clusters. Further, to check whether the difference between any two clusters is significant, multiple comparisons are undertaken using TukeyHSD multiple comparisons of means at the 95% family-wise confidence level. The results show that the differences in some pairs are not significant on an individual variable basis. However, as every cluster has three dimensions of variables, by checking the results of TukeyHSD multiple comparisons for three variables, it can be concluded that the difference in any two clusters is significant at least in one dimension.

3. Estimating Elasticities of Demands for forest products

3.1 Theoretical models

Plywood, fiberboard, particleboard, printing and writing paper, and other paper and paperboard are end products in the forest industry but are inputs in other industries such as building and furniture making. As defined in Varian (1992, p. 28), the function that gives us the optimal choice of inputs as a function of prices is the factor demand function. Considering the cost minimization problem for Cobb-Douglas technology (Varian, 1992, p. 54):

$$c(\boldsymbol{w}, q) = \min \boldsymbol{wy} = \min w_1 y_1 + w_2 y_2 \quad (1)$$

$$\text{such that } A y_1^a \, y_2^b = q$$

where $\boldsymbol{y}$ is the input vector, $\boldsymbol{w}$ is the input price vector and q is the given output. A, a, and b are positive parameters. To solve this problem, the first-order condition is calculated, and the solution for y_1 is:

$$y_1 \, (w_1 \, , w_2 \, , q) = A^{-\frac{1}{a+b}} \left[\frac{a w_2}{b w_1}\right]^{\frac{b}{a+b}} q^{\frac{1}{a+b}}. \quad (2)$$

This formula can be rewritten in the following form for y_1 (Simangunsong and Buongiorno, 2001):

$$y = y(w_1, w_2, q) = \beta_0 \, q^{\beta_1} \left(\frac{w_1}{w_2}\right)^{\beta_2} \quad (3)$$

where β_0, β_1, and β_2 are $A^{-1/(a+b)}$ $(a/b)^{b/(a+b)}$, $1/(a+b)$, and $-b/(a+b)$, respectively. The first input is the particular forest product in this research, and the second input is all other inputs used with the forest product in producing q. Wooldridge (2003) explains that the static model provides a contemporaneous relationship between explanatory variables and the dependent variable. Equation (3) is a static derived demand function as demand adjusts immediately to output and prices. Using the natural logarithm, it takes the following empirical form:

$$\ln(y_{it}) = \ln\beta_0 + \beta_1 \ln(q_{it}) + \beta_2 \ln(p_{it}) + e_{it} \tag{4}$$

where y_{it} is the input demand by country i = 1,…, N during year t = 1,…,T, $p = w_1 / w_2$, is the real price of the forest product, and e_{it} is the error term. By setting $y = y^*$ as the equilibrium demand, conditional on output q and price p, and $0 < \delta \leq 1$ as the speed of adjustment of demand, the adjustment toward equilibrium from one year to the next is represented by the following first-order difference equation:

$$\frac{y}{y_{-1}} = \left(\frac{y^*}{y_{-1}}\right)^{\delta} \tag{5}$$

where y_{-1} is last year's demand. Equation (3) is a special case where $\delta = 1$, implying that full adjustment occurs within one year. By substituting Equation (3) for y^* in Equation (5) and taking the natural logarithm, the short-run dynamic model is:

$$\ln(y_{it}) = \delta\ln\beta_0 + \delta\beta_1 \ln(q_{it}) + \delta\beta_2 \ln(p_{it}) + (1-\delta)\ln\left(y_{i,t-1}\right) + e_{it}^{'} \tag{6}$$

From Equation (6), long-run elasticities can be determined using Simangunsong and Buongiorno (2001):

$$\beta_1 = \frac{\delta\beta_1}{1-(1-\delta)} = \frac{\text{GDP elasticity in eq.(6)}}{1-\text{elasticity of lagged consumption in eq.(6)}}$$

$$\beta_2 = \frac{\delta\beta_2}{1-(1-\delta)} = \frac{\text{price elasticity in eq.(6)}}{1-\text{elasticity of lagged consumption in eq.(6)}} \quad (7)$$

which should match the elasticities in Equation (4). Here, q, output, is proxied by the country's gross domestic product (GDP), and w_2 is proxied by the GDP deflator. As w_1 is the forest product price, p becomes the forest product's real price. The GDP elasticity functions as income elasticity in this research by taking income as aggregate income rather than per capita income, for output is also on a national basis. Regarding this treatment, Baudin and Lundberg (1987) said "the choice of per capita or aggregate data does not really matter".

3.2 Methods and data

In this research, three econometric models were estimated by panel data analysis using TSP software; pooled OLS, fixed effects [least square dummy variables (LSDV)], and random effects. These estimators were applied to three forms of demand equation; long-run static, short-run dynamic, and long-run dynamic. The econometric models take the following forms respectively (Hsiao, 2003; Greene, 2000):

$$y_{it} = \alpha^* + \boldsymbol{\beta}'\boldsymbol{X}_{it} + u_{it} \quad (8)$$

$$y_{it} = \alpha_i^* + \boldsymbol{\beta}'\boldsymbol{X}_{it} + u_{it} \quad (9)$$

$$y_{it} = \alpha^* + \boldsymbol{\beta}'\boldsymbol{X}_{it} + v_i + u_{it} \quad (10)$$

These models contain an individual effect, which is taken to be constant over time t and across country i. We use constant over time t, but it is specific to the individual country i *and* u_{it} is the error term. If both slope and intercept are assumed to be the same across individual countries and over time, as shown in Equation (8), the model is pooled OLS.

Equation (9) is called the within-country regression, or fixed effects, and it assumes different intercepts, α_i^*, but it has the same slope across countries. As for pooled OLS, the fixed effects model is estimated by OLS regression.

The random effects model (Equation 10) assumes that the individual specific effects are uncorrelated with the independent variables but can be taken as a random variable. In equation (10), v_i is a random disturbance. Random effects estimators are generalized least square estimators (GLS).

As demand equations, either static or dynamic, are estimated using the same set of data, it is necessary to measure the goodness of fit, measured by the root mean square error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{NT}\sum_i \sum_t (\hat{y}_{it} - y_{it})^2}$$

Where $\hat{y}_{\text{it}}$ is the predicted demand for country i in year t for N countries and T years; y_{it} is the actual value.

The data were sourced from FAO and the World Bank. The price, in current U.S. dollars, is calculated as the weighted arithmetic average of the unit value of imports and exports. The price is expressed in 2005 U.S. dollars through the following conversion: *Real Price*$_{it}$ = *Current U.S. dollar price*$_{it}$ $\times$ *Exchange rate*$_{it}$ / *GDP Deflator*$_{it}$ / *Exchange rate*$_{i,\,2005}$.

Data from 1992 to 2007 are used because prior to that period, significant institutional changes occurred. For example, some countries gained independence after the Soviet Union collapsed, the former socialist Eastern European countries gave up their socialist systems, China started to move to a socialist market economy, and New Zealand sold much of its state-owned plantation forests.

3.3 Results

3.3.1 Static model

Panel data analysis was applied to every cluster for every forest product. The results of the price and income elasticities of demand for six forest products estimated by the static model based on Equations (4), (8), (9), and (10) are summarized in Table 8. By first comparing the F values and their corresponding critical values for examining country effects and homogeneity of slopes and then checking the Bayesian information criterion or Schwarz Criterion (SBIC), checking the Hausman test statistic, and finally considering the expected signs of the coefficients, the best estimates are chosen and shown in bold letters in Table 8. Table 8 shows that most of the best estimates are chosen from fixed effects estimations. Most of the estimated elasticities are significant at the 1% level. The price elasticities vary from 0.01 to 1.10, where negative sign is omitted and absolute value is being discussed for the convenience of discussion (Pearce, 1992, p. 342). Most elasticities are less than 0.50, and plywood has the widest range of values across clusters. Other paper and paperboard have the smallest price elasticities. Income elasticities range from 0.19 to 3.03. Most of the income elasticities are around 1, but five are over 2.00.

Comparing the elasticity results with the levels of the three variables in the corresponding clusters, it can be found that, even though price elasticities are generally low for most forest products, clusters with high income and consumption levels have higher price elasticities, and that price elasticities decrease with increasing forest coverage. In most cases, clusters with high income and consumption have low-income elasticities. For particleboard, there is no relationship between price and income elasticities and the levels of the three variables describing the clusters.

Except for two clusters, there is serial correlation in all the long-run static models. This result is similar to that in Simangunsong and Buongiorno (2001) and Turner and Buongiorno (2004).

Table 8 Long-run price and income elasticities of demands (Static model)

3.3.2 Dynamic model

The results of the estimation of the dynamic model for short-run demand for six forest products are given in Tables 9 and 10, based on Equations (6), (8), (9) and (10). As for the static model, the best estimates are chosen by comparing the same set of test statistics. The best estimates are shown in bold letters in Tables 9 and 10. Most of the estimates are significant at the 1% level. The price elasticities vary from 0.01 to 0.89. Plywood has the widest range in price elasticities among clusters, from 0.03 to 0.89, showing that demand for plywood is strongly affected by its own price in some countries. Newsprint and other paper and paperboard have the lowest price elasticities. Because there are 19 clusters whose price elasticities are lower than 0.20, it can be seen that demand for these six forest products is price inelastic. As for the income elasticity, there are only two clusters whose income elasticities are over 1; all the others have lower income elasticities, showing that demand is hardly affected by income changes in the short-run. The coefficients of lagged consumption vary from 0.17 to 0.85, so the elasticity of adjustment varies from 0.15 to 0.83.

The problem of first order autocorrelation (AR1) is also tested. The results show that some of the dynamic models corrected first order autocorrelation. Those elasticities from models without serial correlation are shown in italics in Tables 9, 10, 11, and in the Appendix.

Table 9 Short-run price and income elasticities of demands (Dynamic model)

Table 10 Short-run price and income elasticities of demands (Dynamic model) (continued)

From the short-run dynamic estimates of price elasticities, income elasticities, and lagged consumption coefficients, long-run models can be derived based on equation (7). These estimates are shown in Table 11. Most long-run dynamic price elasticities are low, even though some clusters have price elasticities as high as 1.38 or 1.75. Cluster 4 for plywood has a price elasticity of 1.75, showing countries in Cluster 4 have a high price-elastic demand. By checking the list of countries in Cluster 4 for plywood, we find that this cluster consists of countries with high per capita GDP, high forest coverage, and high consumption of plywood, including Japan, Finland, the Republic of Korea, and the United States of America. Most of the income elasticities are around 1. When compared with estimates of the price elasticities and income elasticities in the short-run models, it is easy to see that all the price elasticities in long-run dynamic models have higher values than their short-run counterparts, and most of the income elasticities in long-run dynamic models are higher than their short-run counterparts. These results fit with economic theory, which explains that every input factor can be adjusted in the long run, but only some of the inputs can be adjusted when considered in the short run (Varian, 1992, p. 2-3).

Table 11 Long-run price and income elasticities of demands (Dynamic model)

Comparing the elasticity results with the levels of the three variables in the corresponding clusters, it can be found that in most cases, clusters with high levels of income and consumption have high price elasticities. Forest coverage affects the price elasticities in the opposite direction, i.e., clusters with low forest coverage tend to have high price elasticities.

3.3.3 Root Mean Square Error

To measure the goodness of fit of estimated models, the errors between the observed consumption values and those obtained by the estimated models, Root Mean Square Error (RMSE), are calculated. Table 12 shows the results of RMSE for both long-run static and short-run dynamic models. It shows that all the RMSEs in the dynamic models (short-run) are lower than the corresponding RMSEs in the static models, i.e., dynamic model estimates are superior to static model estimates. Fixed effects model estimates have the smallest RMSEs among all the models with few exceptions; the pooled OLS and random effects estimations are closer, but RMSEs in pooled OLS are lower than those in random effects models in most of the cases, in either static or dynamic models.

Table 12 RMSE（Root Mean Square Error）for static and dynamic estimations

4. Conclusions and discussion

We found that all of the long-run dynamic price elasticities and most of the long-run dynamic income elasticities are higher than their short-run dynamic counterparts. Dynamic model estimations outperform static model estimations as shown in the RMSE statistics, which are in accordance with economic theory (Varian, 1992; Simangunsong and Buongiorno, 2001). In addition, most of the price and income elasticities of demand are significant. The preferred models within either static or dynamic models for a cluster are chosen mainly based on F tests, testing country effects (comparing fixed effects models to pooled OLS), homogeneity of slopes (comparing individual OLS models of heterogeneous intercept and slope to fixed effects models of constant slope and heterogeneous intercept), and the overall homogeneity of pooled data (common intercept and slope), through one-way analysis of covariance. RMSEs are calculated to check the goodness of fit of the models but are not used to select models because the F test has priority as "only one-way analysis of covariance has been widely used" in testing the above stated issues (Hsiao, 2003, p. 15). As for the reason why RMSEs in fixed effects models are lower than those in pooled OLS and random effects models, this might be because fixed effects models assume different intercepts for every individual country, therefore, the number of models have increased in fixed effects, which might cause the RMSEs to become smaller. However, Simangunsong and Buongiorno (2001) produced different results. We think more detailed price and income elasticities of demand estimates are obtained in our research because of the use of cluster analysis prior to panel data analysis.

Hsiao (2003, p. 8) argues that panel data has the ability to isolate the effects of specific actions or policies "based on the assumption that economic data are generated from controlled experiments in which the outcomes are random variables with a probability distribution that is a smooth function of the various variables describing the conditions of the experiment". Micro-economic theory tells us that own price shapes the factor demand curve while other factors, such as output, producers' preferences, and expected future prices, can shift the curve. Of course, it is impossible to put everything into the model. What is important is that the modeling captures the essential forces. When only own price and output are included in models as explanatory variables, other factors, which might be important in some situations, are ignored. Ignoring the individual effects that exist "but not captured by the explanatory variables can lead to parameter heterogeneity in the model specification" (Hsiao, 2003, p. 8). In cluster analysis, by taking per capita GDP, forest coverage, and per capita consumption of the corresponding forest product, countries that are similar in these three variables are grouped together, and panel data analysis is performed based on these clusters. Therefore, better elasticity estimates can be obtained by considering the differences among countries. This treatment considers the inclusion of tastes or preferences and other factors, but does not increase the number of the included explanatory variables.

Silhouette width statistics in the PAM approach indicate that, for every forest product, it is best to group the world into two clusters to get the most stable structure between clusters. But when putting all the countries into a 3-dimensional plot, it is easy to find that there is diversity among countries. As we recognize this diversity and try further to avoid heterogeneity bias, the best determination of the number of clusters to use was based on local maximization, rather than global maximization.

Compared with some previous research, our results show diversity in elasticity estimates and should better reflect the producer behavior affected by own price and output changes because of the cluster analysis. These results will be used in an implementation of the Global Forest Products Model in making long-run projections for forest product demand and supply as part of a research project at the Forestry and Forest Products Research Institute (FFPRI). When similarity among countries is used in estimating elasticities of demand for forest products, better projections are expected. In this research, the way of selecting countries used in the panel data analysis leaves some room for improvement. As the FAO data is improved, more countries can be added to the cluster analysis and better results could be obtained by undertaking this research again.

Acknowledgments

This research is supported and aided financially by Forestry and Forest Products Research Institute (FFPRI), Research grant #200806 of the Forestry and Forest Products Research Institute, the New Zealand Forest Research Institute Ltd. (trading as Scion), and AgResearch Ltd.

References

Atta-Boateng, J., J. W. Jr. Moser, 1998. A method for classifying commercial tree species of an uneven-aged mixed species tropical forest for growth and yield model construction. Forest Ecology and Management 104, 89–99.

Baudin, A., L. Lundberg, 1987. A world model of the demand for paper and paperboard. Forest Science 33 (1), 185-196.

Brooks, D., A. Baudin, P. Schwarzbauer, 1995. Modeling forest products demand, supply and trade. UNECE: FAO Timber and Forest Discussion Papers ECE: TIM: DP: 5. United Nations, Geneva.

Buongiorno, J., 1978. Income and price elasticities in the world demand for paper and paperboard. Forest Science 24 (2), 231-246.

Buongiorno, J., 1979. Income and price elasticities of demand for sawnwood and wood-based panels: a pooled cross-section and time series analysis. Canadian Journal of Forest Research 9, 141–148.

Buongiorno, J., S. Zhu, D. Zhang, J. Turner, D. Tomberlin, 2003. The Global Forest Products Model: Structure, Estimation, and Applications. Academic Press/Elsevier, San Diego.

Chas-Amil M., J. Buongiorno, 2000. The demand for paper and paperboard: econometric models for the European Union. Applied Economics 32, 987–999.

FAO. Global Forest Resources Assessment (FRA 2005). http://www.fao.org/forestry/fra/en/. Accessed on January 20, 2009.

FAO. FAOSTAT. http://faostat.fao.org/site/626/default.aspx#ancor. Accessed on January 20, 2009.

FAO. FAOSTAT. http://faostat.fao.org/site/379/DesktopDefault.aspx?PageID=379. Accessed on April 19, 2011.

Fischer S., R. Dornbusch, R. Schmalensee, 1988. Economics, 2nd edition. McGraw-Hill.

Greene W. H., 2000. Economertic Analysis, 4th edition. Pretice Hall International Inc.

Hsiao C., 2003. Analysis of Panel Data. Cambridge University Press.

Japan Forestry Agency, 2009. Environmentally Friendly Timber Utility Promotion Project (Kankyo ni Yasashi Mokuzai Riyo Suishin Jigyo). http://www.rinya.maff.go.jp/j/forester/f_zigyo/4.html. Accessed on December 21st, 2009.

Kallio M., D. P. Dykstra, C. S. Binkley (Editors), 1987. The global forest sector: an analytical perspective. John Wiley & Sons.

Kaufmann L., P.J. Rousseeuw, 1987. Clustering by means of medoids. In: Proc. Statistical Data Analysis based on the L1 Norm Conf.

Kaufmann L., P.J. Rousseeuw, 1990. Finding Groups in Data: An Introduction to Cluster Analysis. Wiley-Interscience.

Mardia, K. V., J.T. Kent, J.M. Bibby, 1979. Multivariate Analysis. Academic Press.

Michinaka, T., S. Tachibana, J. A. Turner, 2010. Estimating Price and GDP elasticities of demand for sawnwood: Cluster analysis used as a tool in grouping. Journal of Forest Economics 56 (3), 29-36.

Nerlove, M., W. Addison, 1958. Statistical estimation of long-run elasticities of supply and demand. Journal of Farm Economics 40 (4), 861-880.

Roos, A., M. Flinkman, A. Jäppinen, G. Lönner, M. Warensjö, 2001. Production strategies in the Swedish softwood sawmilling industry. Forest Policy and Economics 3-4, 189-197.

Samuelson, P. A., W.D. Nordhaus, 2001. Economics, 17^{th} edition. McGraw-Hill.

Pearce, D., W., 1992. Macmillan Dictionary of Modern Economics. Fourth edition. The Macmillan Press Ltd.

Simangunsong, B.C.H., J. Buongiorno, 2001. International demand equations for forest products: a comparison of methods. Scandinavian Journal of Forest Research 16, 155–172.

Tachibana, S., H. Oka, K. Tamura, 2005. Panel Data Analysis on International Demand for Forest Products, The Role of Forests for Coming Generations -Philosophy and Technology for Forest Resource Management, Japan Society of Forest Planning Press, edited by Kenji Naito, pp. 71-81.

Trømborg, E., J. Buongiorno, B. Solberg, 2000. The global timber market: implications of changes in economic growth, timber supply, and technological change. Forest Policy and Economics 1, 53–69.

Turner, J.A., J. Buongiorno, 2004. Estimating price and income elasticities of demand for imports of forest products from panel data. Scandinavian Journal of Forest Research 19, 358-373.

Varian, H. R., 1992. Microeconomic analysis, 3^{rd} edition. Norton, New York.

World Bank, 2009. World Development Indicators. http://data.worldbank.org/data-catalog/world-development-indicators/.

Yeha, H.-Y., L.C. Wensel, E.C. Turnblom, 2000. An objective approach for classifying precipitation patterns to study climatic effects on tree growth. Forest Ecology and Management 139, 41-50.

Zhu, S., D. Tomberlin, J. Buongiorno, 1998. Global forest products consumption, production, trade and prices: global forest products model projections to 2010. Working Paper GFPOS: WP: 01. FAO, Rome.

Zhu, S., J. Buongiorno, 1999. Global effects of accelerated tariff liberalization in the forest products sector to 2010. Dept of Forest Ecology and Management, Univ. of Wisconsin, Madison.

Zhu, S., J. Buongiorno, J. Turner, R. Raunikar, 2009. Using the Global Forest Products Model (GFPM version 2008), STAFF PAPER SERIES #63. Department of Forest and Wildlife Ecology, University of Wisconsin-Madison.

Appendix

Main results for panel data analysis to sawnwood

Table 1 Region names and their codes

Code	Region	Code	Region	Code	Region	Code	Region
a0	Algeria	e5	Tunisia	j0	Cambodia	n5	Albania
a1	Angola	e6	Uganda	j1	China	n6	Austria
a2	Benin	e7	Congo, Dem Rep.	j2	Cyprus	n7	Belgium
a3	Botswana	e8	Zambia	j3	Hong Kong	n8	Bosnia and Herzegovina
a4	Burkina Faso	e9	Zimbabwe	j4	India	n9	Bulgaria
a5	Burundi	f0	Bahamas	j5	Indonesia	o0	Croatia
a6	Cameroon	f1	Barbados	j6	Iran	o1	Czech
a7	Cape Verde	f2	Belize	j7	Iraq	o2	Denmark
a8	Central Africa	f3	Canada	j8	Israel	o3	Finland
a9	Chad	f4	Cayman Islands	j9	Japan	o4	France
b0	Congo, Rep.	f5	Costa Rica	k0	Jordan	o5	Germany
b1	Côte d'Ivoire	f6	Cuba	k1	Korea, Dem	o6	Greece
b2	Djibouti	f7	Dominica	k2	Korea, Rep.	o7	Hungary
b3	Egypt	f8	Dominican Rep.	k3	Kuwait	o8	Iceland
b4	Equatorial Guinea	f9	El Salvador	k4	Laos	o9	Ireland
b5	Ethiopia	g0	Guatemala	k5	Lebanon	p0	Italy
b6	Gabon	g1	Haiti	k6	Macau	p1	Macedonia
b7	Gambia	g2	Honduras	k7	Malaysia	p2	Malta
b8	Ghana	g3	Jamaica	k8	Mongolia	p3	Netherlands
b9	Guinea	g4	Martinique	k9	Myanmar	p4	Norway
c0	Guinea-Bissau	g5	Mexico	l0	Nepal	p5	Poland
c1	Kenya	g6	Netherlands Antilles	l1	Oman	p6	Portugal
c2	Lesotho	g7	Nicaragua	l2	Pakistan	p7	Romania
c3	Liberia	g8	Panama	l3	Philippines	p8	Slovakia
c4	Libyan Arab Jamahiriya	g9	Saint Vincent/Grenadines	l4	Qatar	p9	Slovenia
c5	Madagascar	h0	Trinidad and Tobago	l5	Saudi Arabia	q0	Spain
c6	Malawi	h1	United States	l6	Singapore	q1	Sweden
c7	Mali	h2	Argentina	l7	Sri Lanka	q2	Switzerland
c8	Mauritania	h3	Bolivia	l8	Syrian Arab	q3	United Kingdom
c9	Mauritius	h4	Brazil	l9	Thailand	q4	Serbia and Montenegro
d0	Morocco	h5	Chile	m0	Turkey	q5	Armenia
d1	Mozambique	h6	Colombia	m1	United Arab Emirates	q6	Azerbaijan
d2	Niger	h7	Ecuador	m2	Viet Nam	q7	Belarus
d3	Nigeria	h8	French Guiana	m3	Yemen	q8	Estonia
d4	Réunion	h9	Guyana	m4	Australia	q9	Georgia
d5	Rwanda	i0	Paraguay	m5	Cook Islands	r0	Kazakhstan
d6	Sao Tome and Principe	i1	Peru	m6	Fiji Islands	r1	Kyrgyzstan
d7	Senegal	i2	Suriname	m7	French Polyn.	r2	Latvia
d8	Sierra Leone	i3	Uruguay	m8	New Caledonia	r3	Lithuania
d9	Somalia	i4	Venezuela	m9	New Zealand	r4	Moldova
e0	South Africa	i5	Afghanistan	n0	Papua New Guinea	r5	Russian Federation
e1	Sudan	i6	Bahrain	n1	Samoa	r6	Tajikistan
e2	Swaziland	i7	Bangladesh	n2	Solomon	r7	Turkmenistan
e3	Tanzania	i8	Bhutan	n3	Tonga	r8	Ukraine
e4	Togo	i9	Brunei Darussalam	n4	Vanuatu	r9	Uzbekistan

Source: Zhu et al. (2009).

Table 2 Results of cluster analysis for plywood

Cluster	Statistics	Per Capita GDP	Forest Cover	Per capita Consumption	Countries in the cluster
1 (25)	mean	3,756	4.7	4.2	a0, b2, ***b3***, ***e0***, ***e4***, i5, ***h2***, ***f9***, ***g1***, ***j6***, ***k0***, r1, k5, ***p2***, c8, d0, g6, d2, ***l1***, ***l2***, ***l5***, l8, ***n3***, ***m0***, r9 (14)
	min	287	0.0	0.1	
	max	16,000	14.1	20.2	
	SD	4,586	4.7	5.5	
2 (34)	mean	3,700	29.6	4.2	n5, a7, a8, ***h5***, ***j1***, ***b1***, o0, f6, ***o1***, ***f8***, ***b8***, g0, ***g2***, ***o7***, ***j4***, ***g3***, ***r3***, p1, ***c5***, ***c6***, ***c9***, ***g5***, ***l3***, ***p5***, ***p7***, ***q4***, d8, ***p8***, l7, e1, ***e3***, ***l9***, ***r8***, ***n4*** (24)
	min	154	16.6	0.0	
	max	13,429	40.2	16.4	
	SD	3,526	6.8	4.9	
3 (25)	mean	3,624	58.2	6.3	a1, ***f2***, ***h4***, a6, ***h6***, ***b0***, f5, ***f7***, m6, ***b7***, c0, h9, ***j5***, k4, ***r2***, ***k7***, k9, g7, g8, ***i1***, ***r5***, ***n1***, ***p9***, ***i2***, ***i4*** (15)
	min	142	42.2	0.0	
	max	18,069	94.7	29.6	
	SD	3,728	12.3	7.6	
4 (25)	mean	31,956	38.0	36.0	***m4***, n6, ***f0***, ***n7***, ***i9***, ***j2***, ***o4***, ***m7***, ***o5***, ***o6***, ***p0***, ***k2***, ***m8***, ***p6***, ***q0***, ***q1***, ***q2***, ***f3***, ***o2***, ***q8***, ***o3***, ***o8***, ***j9***, ***m9***, ***h1*** (24)
	min	11,020	0.5	2.2	
	max	52,401	73.9	131.2	
	SD	10,868	18.1	32.6	
5 (9)	mean	40,461	8.0	34.6	i6, ***f1***, ***o9***, k3, ***p3***, p4, l4, ***m1***, ***q3*** (5)
	min	11,160	0.0	18.9	
	max	76,059	30.7	53.4	
	SD	20,888	9.7	11.2	

Note: please refer to Table 1 for region codes. Those countries that are included in the estimation of demand elasticities are shown in **bold** and *italic* letters.

Table 3 Results of cluster analysis for particleboard

Cluster	Statistics	Per Capita GDP	Forest Cover	Per capita Consumption	Countries in the cluster
1 (30)	mean	4,471	8.4	10.9	i5, a0, ***h2***, ***i6***, ***f1***, a2, ***a7***, ***h5***, ***j1***, b2, b3, ***f9***, ***b5***, g1, ***o7***, ***j6***, ***k0***, ***r0***, c1, ***r1***, k5, ***c4***, ***p2***, c8, ***c9***, ***l1***, ***e0***, n3, ***m0***, ***r8*** (20)
	min	137	0.0	0.0	
	max	19,553	21.6	55.2	
	SD	4,704	8.0	14.8	
2 (13)	mean	42,754	16.0	37.3	***m4***, ***o4***, ***m7***, ***o8***, ***o9***, ***k3***, ***p3***, ***m9***, ***p4***, l4, ***q2***, ***m1***, ***q3*** (12)
	min	25,492	0.0	3.2	
	max	76,059	31.1	65.0	
	SD	15,569	12.9	22.3	
3 (19)	mean	26,805	38.7	100.3	***n6***, ***n7***, ***f3***, ***j2***, ***o1***, ***o2***, ***q8***, ***o3***, ***o5***, ***o6***, ***p0***, ***r3***, ***p5***, ***p6***, ***p8***, ***p9***, ***q0***, ***q1***, ***h1*** (19)
	min	7,685	11.8	47.7	
	max	49,516	73.9	212.6	
	SD	13,399	16.1	37.0	
4 (31)	mean	6,714	41.7	12.4	***f0***, q7, ***f2***, h3, ***h4***, i9, n9, ***h6***, ***o0***, f6, f8, h7, b8, g0, ***g2***, j4, j5, ***g3***, ***j9***, ***k2***, ***r2***, ***p1***, c6, g5, d1, ***m8***, ***g7***, ***i1***, ***p7***, ***r5***, ***q4*** (17)
	min	215	22.8	0.1	
	max	34,331	72.5	48.6	
	SD	8,702	13.5	16.1	

Note: Same as Table 2.

Table 4 Results of cluster analysis for fiberboard

Cluster	Statistics	Per Capita GDP	Forest Cover	Per capita Consumption	Countries in the cluster
1 (34)	Mean	5,108	8.9	7.2	i5, ***a0***, ***h2***, q5, i7, ***f1***, ***a2***, ***j1***, f6, b2, b3, ***f9***, ***o7***, ***j4***, ***j6***, j8, ***k0***, r0, c1, ***p2***, ***d0***, ***g6***, ***l1***, ***l2***, ***l3***, ***l5***, ***q4***, l6, ***e0***, ***l8***, n3, r8, i3, r9 (20)
	Min.	373	0.0	0.1	
	Max.	28,614	26.5	29.7	
	SD	6,530	8.5	7.3	
2 (40)	Mean	7,378	45.3	6.6	n5, ***a1***, ***f0***, f2, ***h3***, n8, ***h4***, ***i9***, n9, ***h6***, b0, m5, f5, ***o0***, f8, m6, ***m7***, ***b7***, o6, ***g2***, j5, ***g3***, ***j9***, ***r2***, ***p1***, ***g5***, k9, ***m8***, ***g7***, ***i1***, ***p6***, ***p7***, ***r5***, n1, d6, d8, h0, n4, ***i4***, ***m2*** (23)
	Min.	142	27.7	0.0	
	Max.	34,331	72.5	21.6	
	SD	8,653	12.2	5.6	
3 (22)	Mean	41,448	25.9	36.4	***m4***, ***n6***, ***n7***, ***f3***, ***o2***, ***o3***, ***o4***, ***o5***, ***o8***, ***o9***, ***p0***, k3, ***p3***, ***m9***, ***p4***, l4, ***q0***, ***q1***, ***q2***, ***m1***, ***q3***, ***h1*** (20)
	Min.	25,057	0.0	14.3	
	Max.	76,059	73.9	65.3	
	SD	12,097	19.8	14.8	
4 (15)	Mean	10,826	33.7	44.1	***i6***, q7, ***h5***, ***j2***, ***o1***, ***q8***, ***k2***, k5, ***r3***, ***k7***, ***c9***, ***p5***, ***p8***, ***p9***, ***m0*** (13)
	Min.	4,022	0.0	25.1	
	Max.	22,483	63.4	118.7	
	SD	6,099	20.1	22.5	

Note: Same as Table 2.

Table 5 Results of cluster analysis for newsprint

Cluster	Statistics	Per Capita GDP	Forest Cover	Per capita Consumption	Countries in the cluster
1 (26)	mean	3,981	5.5	3.1	***a0***, ***h2***, ***i6***, i7, ***f1***, ***b3***, g1, j6, k0, ***k5***, p2, c8, d2, ***d3***, ***l2***, ***l5***, ***e0***, ***l8***, e4, n3, ***e5***, m0, ***r8***, ***i3***, r9, m3 (14)
	min	209	0.0	0.0	
	max	19,553	16.6	14.4	
	SD	4,992	4.9	3.7	
2 (16)	mean	45,284	29.4	35.3	***m4***, ***n6***, ***n7***, ***o2***, ***o3***, ***o5***, ***o8***, ***o9***, ***j9***, ***p3***, ***p4***, l4, ***q1***, ***q2***, ***q3***, ***h1*** (15)
	min	34,331	0.0	3.1	
	max	76,059	73.9	88.3	
	SD	11,879	23.6	18.3	
3 (18)	mean	4,794	59.8	4.2	f2, ***h3***, ***h4***, ***h6***, ***q8***, ***m6***, c0, ***h9***, ***j5***, ***r2***, k7, ***g8***, ***i0***, ***i1***, ***r5***, p9, i2, ***i4*** (13)
	min	231	46.1	0.0	
	max	18,069	94.7	14.2	
	SD	4,299	12.6	4.1	
4 (28)	mean	3,230	28.7	3.0	***n9***, a7, ***h5***, ***j1***, f6, f8, ***b8***, ***g0***, ***j4***, ***g3***, ***r3***, ***p1***, c5, c9, ***g5***, ***d1***, ***g7***, ***l3***, ***p5***, ***p7***, ***q4***, p8, ***l7***, e1, ***l9***, e6, n4, ***m2*** (19)
	min	300	18.0	0.0	
	max	9,739	42.2	12.4	
	SD	2,790	6.8	2.8	
5 (17)	mean	22,712	28.8	14.6	***f3***, ***o0***, ***j2***, ***o1***, ***o4***, ***m7***, ***o6***, ***o7***, ***p0***, ***k2***, ***k3***, g6, ***m9***, ***p6***, ***q0***, ***h0***, m1 (15)
	min	8,769	0.3	7.9	
	max	37,982	63.4	25.4	
	SD	9,026	16.2	5.0	

Note: Same as Table 2.

Table 6 Results of cluster analysis for printing and writing paper

Cluster	Statistics	Per Capita GDP	Forest Cover	Per capita Consumption	Countries in the cluster
1 (33)	mean	3,871	6.0	5.7	i5, ***h2***, q5, ***q6***, ***i6***, ***f1***, a5, b2, b5, ***g1***, k0, ***r0***, ***c1***, r1, ***k5***, c4, ***c7***, ***c8***, g6, ***d2***, ***l1***, ***l2***, l5, ***e0***, ***l8***, e4, n3, ***e5***, m0, ***e6***, ***r8***, i3, r9 (18)
	min	93	0.0	0.0	
	max	19,553	18.0	24.1	
	SD	4,848	5.2	6.4	
2 (22)	mean	2,742	59.3	3.8	a1, i8, h3, ***h4***, ***j0***, ***a6***, ***h6***, ***e7***, ***f5***, ***f7***, ***m6***, ***b6***, b7, ***c0***, ***h9***, ***k9***, ***g8***, n0, i0, ***r5***, i2, ***i4*** (15)
	min	205	45.2	0.1	
	max	6,028	94.72	15.76	
	SD	2,060	13.2	4.2	
3 (22)	mean	37,314	27.7	72.3	***m4***, ***n6***, n7, ***f3***, ***o0***, ***o2***, ***o3***, ***o4***, ***o5***, ***o8***, ***o9***, ***p0***, ***j9***, ***p2***, ***p3***, ***m9***, ***p4***, ***q0***, ***q2***, m1, ***q3***, ***h1*** (20)
	min	8,769	0.0	23.1	
	max	65,825	73.9	107.9	
	SD	12,417	19.2	20.6	
4 (16)	mean	18,350	43.7	32.4	***f0***, ***i9***, ***j2***, ***o1***, ***q8***, ***m7***, ***o6***, ***o7***, ***k2***, ***k7***, ***m8***, ***p5***, ***p6***, ***p8***, p9, q1 (14)
	min	5,865	18.8	5.1	
	max	41,188	66.9	64.4	
	SD	8,816	15.9	17.4	
5 (29)	mean	2,336	30.1	5.1	q7, ***a2***, n8, ***a4***, ***a7***, a8, ***h5***, ***j1***, ***b1***, ***h7***, ***b8***, ***g3***, ***c3***, ***r3***, ***p1***, ***c5***, ***c6***, ***c9***, ***g5***, ***d1***, l0, ***g7***, ***p7***, d6, ***q4***, e1, ***l9***, n4, m2 (21)
	min	215	18.2	0.0	
	max	7,937	42.7	18.8	
	SD	2,383	7.1	6.2	

Note: Same as Table 2.

Table 7 Results of cluster analysis for other paper and paperboard

Cluster	Statistics	Per Capita GDP	Forest Coverage	Per capita Consumption	Countries in the cluster
1 (35)	mean	3,778	6.3	12.6	***i5***, ***a0***, ***h2***, q6, ***f1***, ***a5***, b2,
	min	93	0.0	1.9	b3, f9, b5, ***g1***, j6, ***k0***, r0, ***c1***,
	max	16,000	18.2	42.4	r1, k5, c4, ***c7***, ***p2***, ***c8***, ***c9***,
	SD	4,253	5.4	12.8	g6, d3, ***l1***, ***l2***, ***l5***, ***e0***, ***e4***, ***n3***, ***e5***, m0, r8, ***i3***, ***r9*** (21)
2 (24)	mean	37,779	31.9	113.6	***m4***, ***o2***, ***o4***, ***o8***, ***o9***, ***k3***, ***p3***,
	min	18,069	0.3	35.5	***p4***, ***q2***, m1, ***q3***, ***n6***, ***n7***, ***f3***,
	max	65,825	73.9	234.5	***o3***, ***o5***, ***p0***, ***j9***, ***k2***, m9, p9,
	SD	10,787	22.1	48.8	***q0***, ***q1***, ***h1*** (21)
3 (22)	mean	5,761	60.0	12.5	***f0***, ***f2***, ***h3***, ***h4***, i9, ***j0***, ***h6***, ***f7***,
	min	231	43.4	0.1	***q8***, ***m6***, b6, c0, ***h9***, ***j5***, ***k7***,
	max	24,860	94.7	54.2	g4, ***k9***, ***i1***, ***r5***, n1, i2, ***i4*** (16)
	SD	6,487	12.8	13.7	
4 (25)	mean	1,497	33.0	7.8	q7, ***a2***, n8, a4, a6, a7, b1,
	min	154	20.7	0.2	f8, ***h7***, q9, ***b8***, g2, ***j4***, ***g3***,
	max	4,926	45.2	27.0	c3, ***p1***, ***c6***, ***d1***, l0, ***g7***, ***p7***,
	SD	1,350	7.8	9.7	d7, d8, **l7**, **m2** (12)
5 (21)	mean	11,395	31.8	48.3	***n9***, ***h5***, ***j1***, f5, ***o0***, ***j2***, ***o1***,
	min	905	8.0	8.6	***m7***, ***o6***, ***o7***, j8, ***r2***, ***r3***, ***g5***,
	max	26,468	47.6	76.8	m8, ***p5***, ***p6***, ***q4***, ***p8***, ***l9***, ***h0***
	SD	7,583	10.0	17.9	(18)

Note: Same as Table 2.

Table 8 Long-run price and GDP elasticities of demands (Static model)

Item	Variable	Method	1	2	3	4	5
Ply-wood	Price						
		Pooled OLS	-0.37	-0.18	-0.24	-1.23	-0.61
		LSDV	-0.42	**-0.06***	**-0.01*****	-1.08	**-0.86**
		Random effects	**-0.40**	-0.08	-0.02***	**-1.10**	-0.70
	GDP						
		Pooled OLS	0.92	1.02	0.83	0.97	0.72
		LSDV	0.67**	**1.50**	**0.51***	1.01	**0.19*****
		Random effects	**0.89**	1.17	0.74	**0.98**	0.66
Particle-board	Price						
		Pooled OLS	-0.30	-1.11	0.10***	-0.10**	
		LSDV	**-0.38**	**-0.96**	**-0.06*****	**-0.05*****	
		Random effects	-0.39	-0.88	-0.14	-0.09	
	GDP						
		Pooled OLS	1.34	1.19	0.83	1.17	
		LSDV	**2.24**	**0.38***	**1.52**	**2.32**	
		Random effects	1.63	0.76	0.97	1.49	
Fiber-board	Price						
		Pooled OLS	-0.75	**-0.14**	**-0.40**	-0.25	
		LSDV	**-0.64**	0.03***	0.23***	**-0.13***	
		Random effects	-0.78	-0.08	-0.04***	-0.31***	
	GDP						
		Pooled OLS	1.04	**0.99**	**0.95**	1.05	
		LSDV	**2.73**	3.74	2.00	**3.03**	
		Random effects	1.54	1.25	1.08	1.51***	
News-print	Price						
		Pooled OLS	-0.17*	**-0.44**	**-0.04*****	-0.24	-0.59
		LSDV	-0.16	0.13***	-0.07	-0.18	**-0.98**
		Random effects	**-0.16**	0.21***	-0.06*	**-0.19**	-0.86
	GDP						
		Pooled OLS	1.04	**1.05**	**0.91**	1.05	0.99
		LSDV	1.45	0.54	0.03	1.19	**0.31*****
		Random effects	**1.22**	1.03	0.92	**1.10**	0.87
Printing and writing paper	Price						
		Pooled OLS	-0.46	-0.22	-0.48	-0.19**	-0.41
		LSDV	**-0.41**	**-0.04****	**-0.79**	**-0.66**	-0.42
		Random effects	-0.43	-0.05*	-0.67	-0.50	**-0.42**
	GDP						
		Pooled OLS	1.45	1.13	1.03	1.45	1.28
		LSDV	**1.95**	**1.76**	**0.45**	**0.66**	1.25
		Random effects	1.59	1.14	0.97	1.27	**1.28**
Other paper and paper-board	Price						
		Pooled OLS	-0.55	-0.79	-0.17	**-0.12*****	-0.02***
		LSDV	**-0.33**	**-0.31**	**-0.05*****	0.11**	-0.04*
		Random effects	-0.33	-0.15	-0.08	-0.01***	**-0.04***
	GDP						
		Pooled OLS	1.27	1.20	1.17	**1.33**	1.22
		LSDV	**1.05**	**0.48**	**1.70**	2.53	1.20
		Random effects	1.23	0.96	1.21	1.80	**1.20**

Note: Numbers 1, 2, 3, 4 and 5 in the column header refer to country clusters. Numbers in bold letters are best estimations, judged by F values, coefficient signs, Hausman Test, and SBIC. $^{***}p>0.10$; $^{**}p<0.10$; $^{*}p<0.05$; while all others $p<0.01$.

Table 9 Short-run price and GDP elasticities of demands (Dynamic model)

Item	Variable	Method	1	2	3	4	5
Ply-wood	Price						
		Pooled OLS	-0.22	**-0.11**	-0.08	**-0.89**	-0.49
		LSDV	-0.37	-0.13	**-0.03*****	-1.05	**-0.73**
		Random effects	***-0.32***	-0.12	-0.06***	-1.04	-0.57
	GDP						
		Pooled OLS	0.27	**0.15**	0.16*	**0.50**	0.33
		LSDV	0.50***	0.50	**0.51****	0.86	**0.13*****
		Random effects	***0.45***	0.25	0.40	0.69	0.45
	Lagged Consumption						
		Pooled OLS	0.72	**0.85**	0.81	**0.49**	0.55
		LSDV	0.39	0.52	**0.17***	0.22	**0.25**
		Random effects	***0.52***	0.75	0.50	0.30	0.36
Particle-board	Price						
		Pooled OLS	**-0.15**	-0.39	0.02***	-0.05*	
		LSDV	-0.34	**-0.70**	***-0.01******	-0.11	
		Random effects	-0.25	-0.47	-0.01***	***-0.11***	
	GDP						
		Pooled OLS	**0.21**	0.10	0.04***	0.12	
		LSDV	0.81	**0.25*****	***0.62***	1.37	
		Random effects	0.43***	0.27	0.10	***0.44***	
	Lagged Consumption						
		Pooled OLS	**0.84**	0.89	0.95	0.87	
		LSDV	0.51	**0.42**	***0.64***	0.34	
		Random effects	0.67	0.75	1.29	***0.62***	
Fiber-board	Price						
		Pooled OLS	-0.30	**-0.11**	**-0.01*****	-0.10*	
		LSDV	-0.58	-0.08	0.37*	-0.13*	
		Random effects	***-0.54***	-0.12	0.08***	***-0.15***	
	GDP						
		Pooled OLS	0.19	**0.22**	**0.32**	0.27	
		LSDV	1.32	1.25	1.12	1.39	
		Random effects	***0.40***	0.31	0.41	***0.37***	
	Lagged Consumption						
		Pooled OLS	0.80	**0.78**	**0.68**	0.74	
		LSDV	0.46	0.54***	0.48	0.49	
		Random effects	***0.61***	0.70	0.60	***0.67***	
News-print	Price						
		Pooled OLS	-0.10*	**-0.04*****	-0.02***	0.00***	0.14***
		LSDV	-0.21	0.00***	***-0.06****	***-0.08*****	**-0.18**
		Random effects	***-0.19***	0.07***	-0.03***	-0.07*	-0.09***
	GDP						
		Pooled OLS	0.27	**0.28**	0.54	0.20	0.31
		LSDV	1.04	0.15***	***0.37****	***1.05***	**0.63**
		Random effects	***0.75***	0.48	0.68	0.60	0.65
	Lagged Consumption						
		Pooled OLS	0.73	**0.72**	0.39	0.81	0.69
		LSDV	0.13*	0.38	***0.19***	**0.27**	**0.26**
		Random effects	***0.28***	0.52	0.23	0.45	0.34

Note: Numbers in bold letters are best estimations, judged by F values, coefficient signs, Hausman Test, SBIC, and rho values for first order autocorrelation (AR1). Numbers in italics are those with insignificant rho values. $^{***}p>0.10$; $^{**}p<0.10$; $^{*}p<0.05$; while all others $p<0.01$.

Table 10 Short-run price and GDP elasticities of demands (Dynamic model) (continued)

Item	Variable	Method	1	2	3	4	5
Printing and writing paper	Price						
		Pooled OLS	-0.21	-0.11	-0.12***	-0.21	-0.27
		LSDV	***-0.40***	-0.08	-0.62	**-0.69**	-0.39
		Random effects	-0.33	***-0.10***	***-0.29***	-0.40	***-0.33***
	GDP						
		Pooled OLS	0.48	0.30	0.25	0.29	0.63
		LSDV	***1.05***	1.12	-0.19***	**0.18*****	0.82
		Random effects	0.74	***0.47***	***0.39***	0.83	***0.78***
	Lagged Consumption						
		Pooled OLS	0.66	0.75	0.73	0.79	0.50
		LSDV	***0.35***	0.42	0.48	**0.24**	0.29
		Random effects	0.49	***0.59***	***0.58***	0.38	***0.38***
Other paper and paper-board	Price						
		Pooled OLS	-0.07	-0.06***	-0.08	-0.04***	-0.07*
		LSDV	***-0.14***	***-0.16***	-0.08*	0.07***	**-0.10**
		Random effects	-0.10	-0.03***	***-0.09***	***-0.04******	-0.08
	GDP						
		Pooled OLS	0.23	0.08	0.22	0.21	0.07*
		LSDV	***0.61***	***0.08******	0.57	1.66	**0.75**
		Random effects	0.46	0.22	***0.34***	***0.50***	0.32
	Lagged Consumption						
		Pooled OLS	0.82	0.93	0.81	0.83	0.94
		LSDV	***0.46***	***0.53***	0.56	0.36	**0.32**
		Random effects	0.64	0.80	***0.71***	***0.64***	0.73

Note: Same as Table 9.

Table 11 Long-run price and GDP elasticities of demands (Dynamic model)

Item	Variable	Method	1	2	3	4	5
Ply-wood	Price						
		Pooled OLS	-0.79	**-0.73**	-0.42	**-1.75**	-1.09
		LSDV	-0.61	-0.27	**-0.04**	-1.35	**-0.97**
		Random effects	***-0.67***	-0.48	-0.12	-1.49	-0.89
	GDP						
		Pooled OLS	0.96	**1.00**	0.84	**0.98**	0.73
		LSDV	0.31	0.39	**0.49**	0.37	**0.07**
		Random effects	***0.94***	1.00	0.80	0.99	0.70
Particle-board	Price						
		Pooled OLS	**-0.94**	-3.55	0.40	-0.38	
		LSDV	-0.69	**-1.21**	***-0.03***	-0.17	
		Random effects	-0.76	-1.88	0.03	***-0.29***	
	GDP						
		Pooled OLS	**1.31**	0.91	0.80	0.92	
		LSDV	0.48	**0.11**	***0.60***	1.17	
		Random effects	1.30	1.08	-0.34	***1.16***	
Fiber-board	Price						
		Pooled OLS	-1.50	**-0.50**	**-0.03**	-0.38	
		LSDV	-1.07	-0.17	0.71	-0.25	
		Random effects	***-1.38***	-0.40	0.20	***-0.45***	
	GDP						
		Pooled OLS	0.95	**1.00**	**1.00**	1.04	
		LSDV	0.64	1.06	3.88	1.11	
		Random effects	***1.03***	1.03	1.03	***1.12***	
News-print	Price						
		Pooled OLS	-0.37	**-0.14**	-0.03	0.00	0.45
		LSDV	-0.24	0.00	***-0.07***	***-0.11***	**-0.24**
		Random effects	***-0.26***	0.15	-0.04	-0.13	-0.14
	GDP						
		Pooled OLS	1.00	**1.00**	0.89	1.05	**1.00**
		LSDV	0.84	0.15	***0.34***	***0.95***	**0.85**
		Random effects	***1.04***	1.00	0.88	1.09	0.98
Printing and writing paper	Price						
		Pooled OLS	-0.62	-0.44	-0.44	-1.00	-0.54
		LSDV	***-0.62***	-0.14	-1.19	**-0.91**	-0.55
		Random effects	-0.65	***-0.24***	***-0.69***	-0.65	***-0.53***
	GDP						
		Pooled OLS	1.41	1.20	0.93	1.38	1.26
		LSDV	***0.65***	0.98	-0.09	**0.09**	0.53
		Random effects	1.45	***1.15***	***0.93***	1.34	***1.26***
Other paper and paper-board	Price						
		Pooled OLS	-0.39	-0.86	-0.42	-0.24	-1.17
		LSDV	***-0.26***	-0.34	-0.18	0.11	**-0.15**
		Random effects	-0.28	**-0.15**	***-0.31***	***-0.11***	-0.30
	GDP						
		Pooled OLS	1.28	1.14	1.16	1.24	1.17
		LSDV	***0.48***	0.06	0.48	1.86	**0.65**
		Random effects	1.28	**1.10**	***1.17***	***1.39***	1.19

Note: Same as Table 9.

Table 12 RMSE（Root Mean Square Error）for static and dynamic estimations

Item	Type	Method	1	2	3	4	5
Ply-wood	Static						
		Pooled OLS	1.227	1.225	1.409	0.838	0.458
		LSDV	0.761	0.603	0.653	0.610	0.314
		Random effects	1.228	1.266	1.532	0.841	0.481
	Dynamic						
		Pooled OLS	0.774	0.550	0.786	0.693	0.341
		LSDV	0.676	0.499	0.639	0.586	0.289
		Random effects	0.813	0.564	0.915	0.717	0.356
Particle-board	Static						
		Pooled OLS	1.813	1.145	0.498	1.611	
		LSDV	0.969	0.359	0.242	0.617	
		Random effects	1.890	1.400	0.588	1.775	
	Dynamic						
		Pooled OLS	0.853	0.379	0.216	0.650	
		LSDV	0.740	0.323	0.197	0.520	
		Random effects	0.907	0.417	0.219	0.780	
Fiber-board	Static						
		Pooled OLS	1.484	1.297	0.715	0.839	
		LSDV	0.785	0.825	0.547	0.548	
		Random effects	1.719	1.424	0.737	1.074	
	Dynamic						
		Pooled OLS	0.734	0.737	0.527	0.502	
		LSDV	0.616	0.674	0.488	0.456	
		Random effects	0.792	0.745	0.532	0.507	
News-print	Static						
		Pooled OLS	0.933	0.465	0.526	0.984	0.814
		LSDV	0.471	0.324	0.451	0.502	0.454
		Random effects	0.958	0.490	0.527	0.988	0.841
	Dynamic						
		Pooled OLS	0.508	0.302	0.399	0.528	0.498
		LSDV	0.370	0.257	0.338	0.415	0.370
		Random effects	0.663	0.319	0.409	0.638	0.582
Printing and writing paper	Static						
		Pooled OLS	1.040	1.082	0.540	0.900	0.908
		LSDV	0.694	0.695	0.437	0.448	0.726
		Random effects	1.061	1.159	0.637	0.951	0.908
	Dynamic						
		Pooled OLS	0.693	0.655	0.353	0.559	0.686
		LSDV	0.610	0.578	0.359	0.427	0.622
		Random effects	0.720	0.685	0.426	0.677	0.696
Other paper and paper-board	Static						
		Pooled OLS	1.191	0.498	0.931	1.117	0.933
		LSDV	0.628	0.205	0.565	0.534	0.258
		Random effects	1.218	0.663	0.951	0.311	0.934
	Dynamic						
		Pooled OLS	0.594	0.183	0.490	0.581	0.289
		LSDV	0.517	0.157	0.447	0.499	0.233
		Random effects	0.636	0.195	0.499	0.624	0.350

Appendix

Main results for panel data analysis to sawnwood

Variable	Method	1	2	3	4	5	6	7
		Elasticities for long-run static models						
Price								
	Pooled OLS	-0.11	0.04	-0.21	-0.16	-0.37	-0.48	-0.26
	LSDV	-0.07	**-0.02*****	**-0.02*****	**-0.57**	**-0.13*****	-0.32	-0.49
	Random effects	**-0.07*****	0.01	-0.02	-0.33	-0.39	**-0.34**	**-0.50**
GDP								
	Pooled OLS	1.24	1.01	0.97	0.99	0.81	1.11	0.77
	LSDV	1.12	**0.65**	**0.40****	**0.32**	**2.38**	1.34	1.05
	Random effects	**1.20**	0.91	0.79	0.85	0.89	**1.25**	**0.85**
		Elasticities for short-run dynamic models						
Price								
	Pooled OLS	-0.10	-0.02	-0.03**	**-0.12**	-0.34	***-0.09******	-0.29
	LSDV	***-0.11***	***-0.04***	***-0.02***	-0.46	***-0.34***	0.16	**-0.46**
	Random effects	-0.06	-0.02	-0.03	-0.20	-0.36	0.00	-0.40
GDP								
	Pooled OLS	0.57	0.19	0.08	**0.15**	0.15	***0.33***	0.12
	LSDV	***0.21******	***0.36***	***0.13***	0.09	***0.76***	1.67	**0.75**
	Random effects	0.59	0.40	0.14	0.30	0.17	0.98	0.28
Lagged Consumption								
	Pooled OLS	0.48	0.81	0.90	**0.84**	0.79	***0.68***	0.83
	LSDV	***0.24***	***0.39***	***0.61***	0.42	***0.64***	0.18	**0.41**
	Random effects	0.25	0.60	0.84	0.69	0.78	0.31	0.63
		Elasticities for long-run dynamic models						
Price								
	Pooled OLS	-0.19	-0.12	-0.28	**-0.79**	-1.63	***-0.27***	-1.75
	LSDV	***-0.14***	***-0.06***	***-0.05***	-0.79	***-0.95***	0.19	**-0.78**
	Random effects	-0.09	-0.05	-0.18	-0.63	-1.61	0.00	-1.10
GDP								
	Pooled OLS	1.10	0.98	0.80	**0.97**	0.73	***1.02***	0.74
	LSDV	***0.27***	***0.60***	***0.33***	0.15	***2.11***	2.05	**1.26**
	Random effects	0.79	0.98	0.85	0.95	0.74	1.42	0.76
		RMSE						
Static								
	Pooled OLS	0.778	0.969	1.156	0.318	0.647	0.496	0.693
	LSDV	0.665	0.165	0.219	0.152	0.470	0.324	0.332
	Random effects	0.780	0.986	1.307	0.414	0.674	0.509	0.718
Dynamic								
	Pooled OLS	0.042	0.558	0.398	0.161	0.373	0.365	0.348
	LSDV	0.281	0.486	0.360	0.136	0.358	0.275	0.299
	Random effects	0.605	0.595	0.407	0.170	0.374	0.447	0.378

Note: Numbers in bold letters are best estimations, judged by F values, coefficient signs, Hausman Test, SBIC, and rho values for first order autocorrelation (AR1). Numbers in italics are those with insignificant rho values. For static and short-run elasticities in bold letters, ***p>0.10; **p<0.10; *p <0.05; while all others p<0.01.

Source: Michinaka et al. (2010). AR(1) was not considered in choosing best estimations in Michinaka et al. (2010).