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Short-term forecasts of selected wood product sales volumes

Method and assumptions

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Summary

Forest and Wood Products Australia (FWPA) commissioned ABARES to develop quarterly sales volume forecasts for selected wood products. Reliable sales forecasts are critical to informing decisions on production, inventory management and personnel. The forecasts use the FWPA Softwood data series, which provides monthly sales volumes for 44 product categories. The series was established in 2002 by Australia's major softwood sawmilling companies.

ABARES was commissioned to provide forecasts for four wood products: untreated structural pine less than 120 millimetres thick, untreated structural pine greater than 120 millimetres thick, termite-treated structural pine and landscape wood products. This report documents the methods and assumptions underlying the ABARES forecasting models.

The econometric models estimated in this report are not based on any formal structural economic models of the relevant wood product markets. They are simple, statistically robust, predictive models based on historical relationships and patterns observed over the March 2002 to March 2016 sample period.

In building the econometric models, ABARES first estimated a large number of candidate models with various functional forms and explanatory variables over the March 2002 to December 2012 training period. Pure time series terms, including seasonal effects, trends and moving average terms, were considered and in many cases found to be useful predictors of future sales. The statistical robustness of the candidate models was verified using formal diagnostic tests.

ABARES then validated the out-of-sample forecasting performance of the candidate models by comparing forecasts with actual sales over the March 2013 to December 2015 validation period. Forecasting performance was assessed on the basis of point accuracy, measured using the root mean squared error, and directional accuracy, measured as the rate of success in predicting whether sales move up or down in a given quarter. Where it was unclear which model or combination of models should be chosen, priority was placed on point forecasting accuracy as opposed to directional accuracy.

The final models do not include all of the many factors that were hypothesised to affect wood product sales because they were found to be statistically insignificant or resulted in less accurate out-of-sample forecasts. As a result, the final models are relatively simple compared with the range of models estimated.

The FWPA Softwood data series does not include all producers in the industry, and the number of participating producers changes over time. As a result, the series is not representative of national production or sales and the effects of new entrants in the data series could affect the validity of the estimated models.

Forecasting is an evolving process whereby models are continually refined in response to new information and lessons learnt. ABARES will continue to review the models estimated in this study to improve the accuracy of the forecasts over time.

1 Introduction

Forest and Wood Products Australia (FWPA) commissioned ABARES to provide quarterly sales volume forecasts for selected wood products, using data contained in the FWPA Softwood data series. The FWPA Softwood data series includes a range of outdoor and structural wood products. ABARES was commissioned to provide forecasts for four wood products from the series: landscape wood products, termite-treated structural pine, untreated structural pine less than 120 millimetres, and untreated structural pine greater than 120 millimetres (Table 1).

Table 1 Selected wood products

Wood product sales series	Description	Typical uses	Sales in 2015 (m^3)
Landscape wood products	Sleeper and retaining wall material	Sleeper and retaining wall material	152 500
Termite-treated structural pine	Treated, seasoned (kiln or air dried), pine structural framing between 70 x 35 mm and 140 x 45 mm, MGP or F grades	Suitable for inside, above-ground uses (such as framing and flooring) or other similar uses in dry conditions.	574 500
Category 1 Untreated structural pine less than 120 mm	Untreated, seasoned (kiln or air dried), pine structural framing, between 70 x 35 mm and 90 x 45 mm, MGP or F grades	Residential frame construction (wall frames: studs, plates, headers; floor and roof truss components) and other internal fit-out elements	730 600
Category 2 Untreated structural pine greater than 120 mm	Untreated, seasoned (kiln or air dried), pine structural framing, between 120 x 35 mm and 290 x 45 mm, MGP or F grades	Residential frame construction (wall frames: studs, plates, headers; floor and roof truss components) and other internal fit-out elements	70 600

Sources: FWPA Softwood data series

Most empirical studies of wood product markets aim to better understand drivers for demand, supply or prices. The focus of this study is to develop models that can produce reliable and timely forecasts of sales volumes to support decision-making by industry. Short-term forecasting is a relatively small area of academic research and is more commonly undertaken by industry. However, where short-term forecasting exercises are undertaken, the focus is often on wood product prices as opposed to volumes, and the methods and assumptions behind industry forecasts are rarely made public.

This report documents the methods and assumptions underlying ABARES forecasting models and procedures. The discussion focuses on characteristics of key datasets and the procedures used to identify, validate and implement the forecasting models.

The broad approach to developing the ABARES forecasting models was to first estimate a large number of candidate models with robust in-sample properties and then validate their out-of-sample forecasting performance using a subset of the data. The estimated models include exogenous explanatory variables such as house commencements and past sales, as well as pure time series terms such as trends, seasonal effects and moving averages.

As far as the authors are aware, the FWPA Softwood data series has not been used in any formal econometric analysis. For this reason, ABARES conducted extensive preliminary testing around the presence of stochastic trends to inform the modelling exercise.

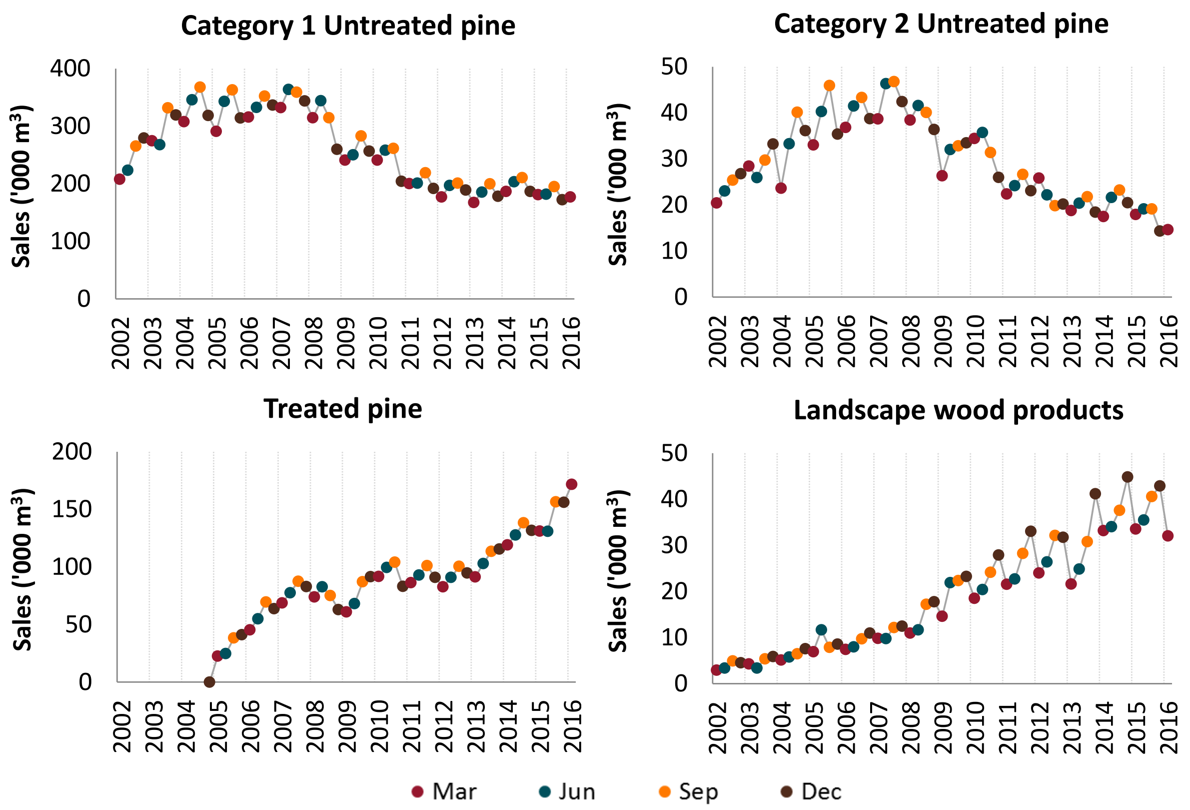
2 Data exploration

The FWPA Softwood data series was established in 2002 by Australia's major softwood sawmilling companies. The data series provides monthly sales volumes for 44 detailed wood product categories, amounting to over 2.5 million cubic metres a year. The data series does not estimate total industry production. FWPA estimates that the market coverage of the series was around 80 per cent in 2013–14. However, these estimates are subject to several assumptions, including changes in inventory levels and actual versus nominal volumes.

Historic sales

Sales of category 1 and category 2 untreated pine increased from 2002, before declining from 2008 onward (Figure 1). A likely explanation for the long-term decline in sales of untreated structural pine is its substitution by termite-treated structural pine (here on referred to as treated pine). Sales of treated pine have increased, on average, by 4.7 per cent a quarter (around 20 per cent a year) since 2005. Sales of landscape wood products have also increased steadily since 2002, with an average quarterly growth rate of 4.3 per cent (around 18 per cent a year).

Figure 1 Quarterly sales of selected wood products, March quarter 2002 to March quarter 2016



Source: FWPA Softwood data series

Seasonality

With quarterly data, seasonal effects can be powerful predictors of movements in the short term. All four sales series exhibit some degree of seasonality over the sample period, with regular peaks and troughs. However, the seasonal cycles differ in pattern, magnitude and consistency across the four series and over time (Figure 1). For example, sales of total structural pine tend to be highest in the September quarters and lowest in the March quarters, which is consistent with the seasonal cycle of house commencements. In contrast, sales of landscape wood products tend to increase over the calendar year.

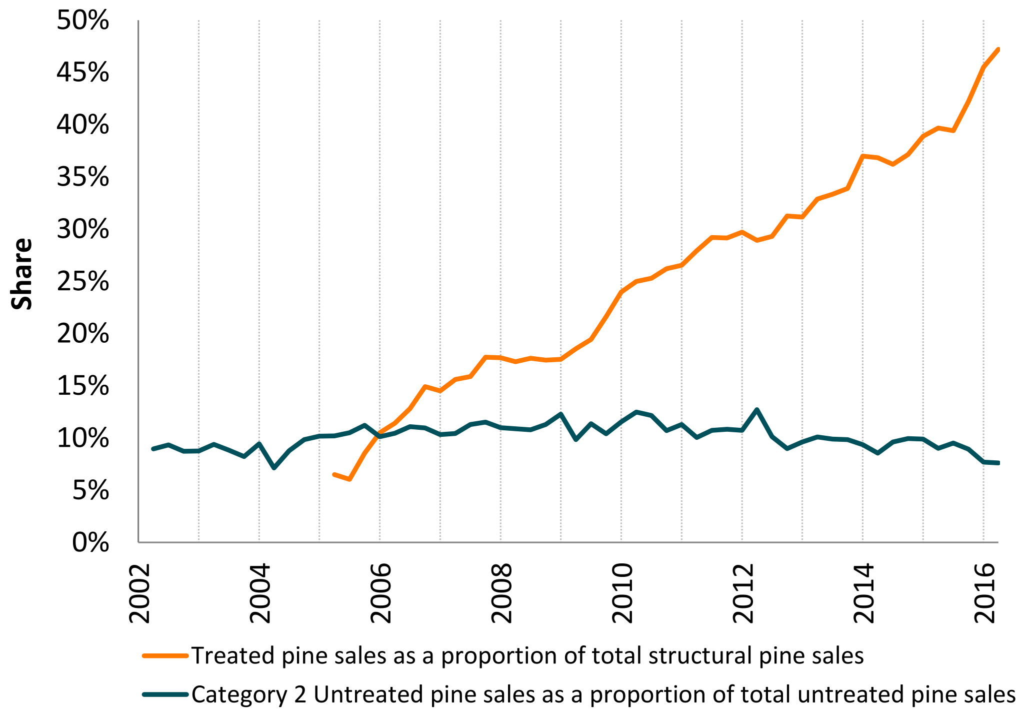
The seasonal cycle in landscape wood products is more consistent over the sample period than that for structural pine. For example, in nine of the 14 full calendar years from March 2002 to December 2015, sales of landscape wood products were highest in December and lowest in March. In only six of the 14 years were sales of either category of untreated pine highest in September and lowest in March.

The magnitude of the seasonal peaks and troughs, relative to sales, also changes over time. In the case of untreated pine, in particular category 1 untreated pine, the magnitude of seasonal peaks and troughs is decreasing. In contrast, the variation in sales between quarters is increasing for landscape wood products. However, when measured relative to the level of sales, which is increasing over time, the variation in landscape wood products sales across seasons is decreasing.

Relative sales

Of particular interest for modelling interactions between the four series are the relative levels of sales over time. For example, the share of treated pine as a proportion of total structural pine sales (comprising treated pine, category 1 untreated pine, and category 2 untreated pine sales) has increased almost linearly over time (Figure 2). This is characteristic of an emerging market.

Figure 2 Share of treated pine as a proportion of total structural pine sales and share of category 2 sales as a proportion of untreated pine sales, March quarter 2002 to March quarter 2016



Source: FWPA Softwood data series

In contrast, the share of category 2 sales as a proportion of total untreated sales (comprising category 1 and category 2 untreated pine sales) has been relatively stable. This suggests a possible substitution between treated and untreated pine products and complementarity between the two categories of untreated pine. The proportion of untreated pine sales attributed to category 2 untreated pine is likely a function of demand-side factors such as house design and supply-side factors, such as log size and shape, and sawing methods. These are unlikely to change significantly over the short-term.

Outliers

Figure 3 provides an alternative way of examining seasonal patterns in the four series and is useful for identifying potential outliers. A number of observations appear to contradict the typical seasonal pattern. For example, sales of category 1 and category 2 untreated pine increased in December 2002 despite decreasing in the December quarter of almost all other years. Similarly, sales of treated pine increased in December of 2005 and 2009 despite decreases in all other years. Decreases in sales of category 1 and treated pine in September 2008 also appear to be outliers but this may be explained by an uncharacteristic decrease in house commencements at the time.

Some observations that follow the seasonal pattern exhibit exceptionally larger changes than other years, particularly in landscape wood products sales. For example, in June 2005 landscape wood products sales increased by almost 70 per cent over the previous quarter. Similarly, in September 2004, sales of category 2 untreated pine increased over 40 per cent. These types of outliers may be the result of company- or even mill-specific factors or the introduction of new companies in the data series (see Discussion and limitations for further information).

Short-term drivers of sales

The key drivers of wood product sales in the short run are likely to differ from those in the long run. For example, factors such as the number of mills and wood supply are fixed in the short to medium term. They are therefore unlikely to explain variations in sales over shorter time horizons. Instead, seasonal patterns, trends and past sales are expected to explain a large proportion of variations in sales over shorter time horizons.

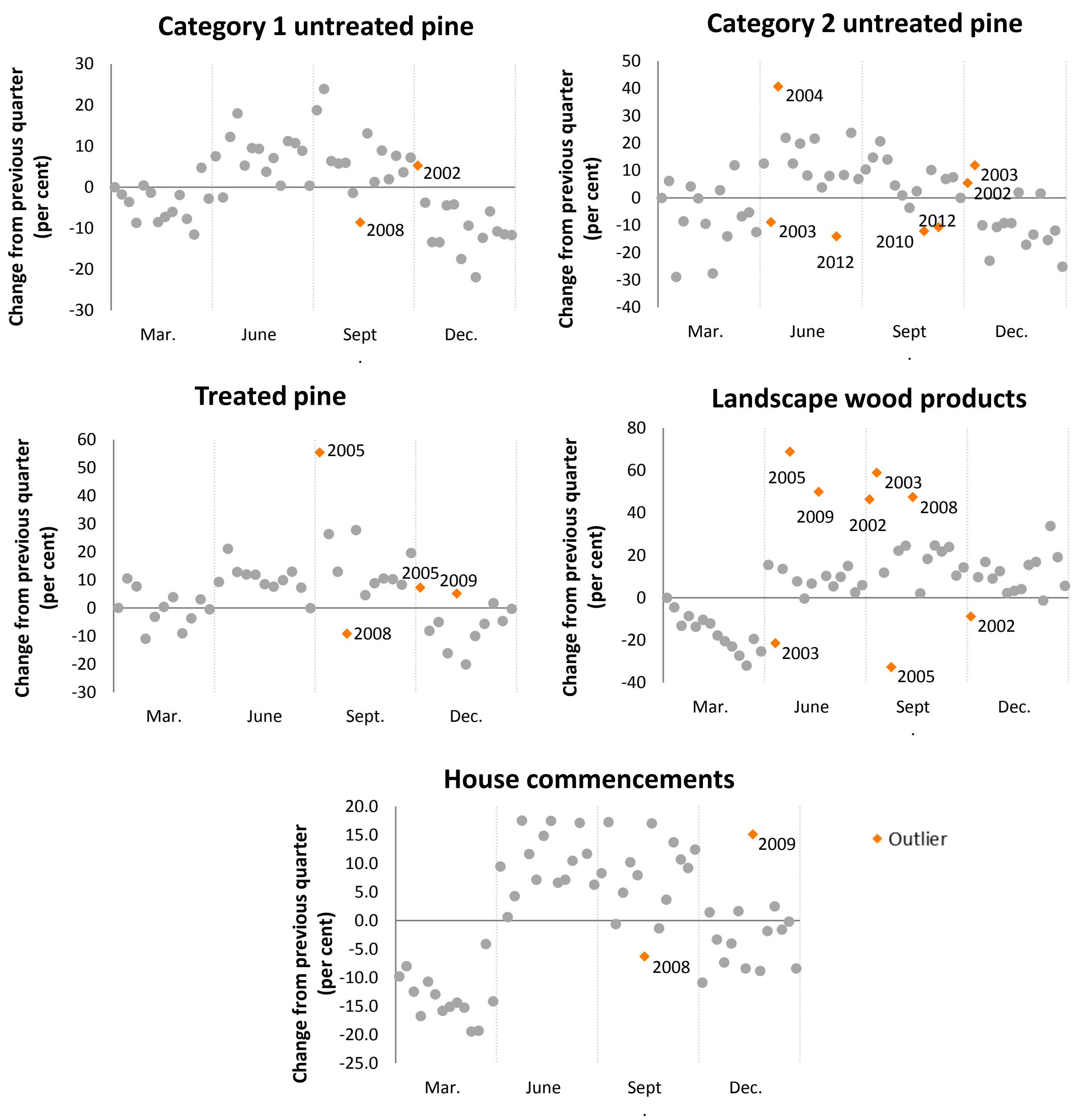
Production of sawnwood

Many processors have long-term wood supply arrangements in place that prevent significant fluctuations in log availability and costs of production. Harvesters plan their operations to meet these contractual obligations over the medium term, but there may still be unforeseen factors that constrain supply on a quarterly basis. In many cases, these constraints are location specific and not observed, making them difficult to account for in the types of national-level models used in this report. Consequently, most of the drivers of sales considered in this report are demand-side factors. However, ABARES has considered the potential for input costs to affect supply in the short term by including a sawmill input price index and a road transport price index in the candidate model equations.

Demand for sawnwood

Demand for softwood timber is assumed to be primarily a function of house and other residential commencements. However, analysis of the data shows that the relationship between residential commencements and total structural pine sales were weak over the medium term between 2002 and 2007 (Figure 4). In particular, total structural pine sales increased by almost 13 per cent a year before 2008 while new residential commencements remained steady at around 160 000 per year.

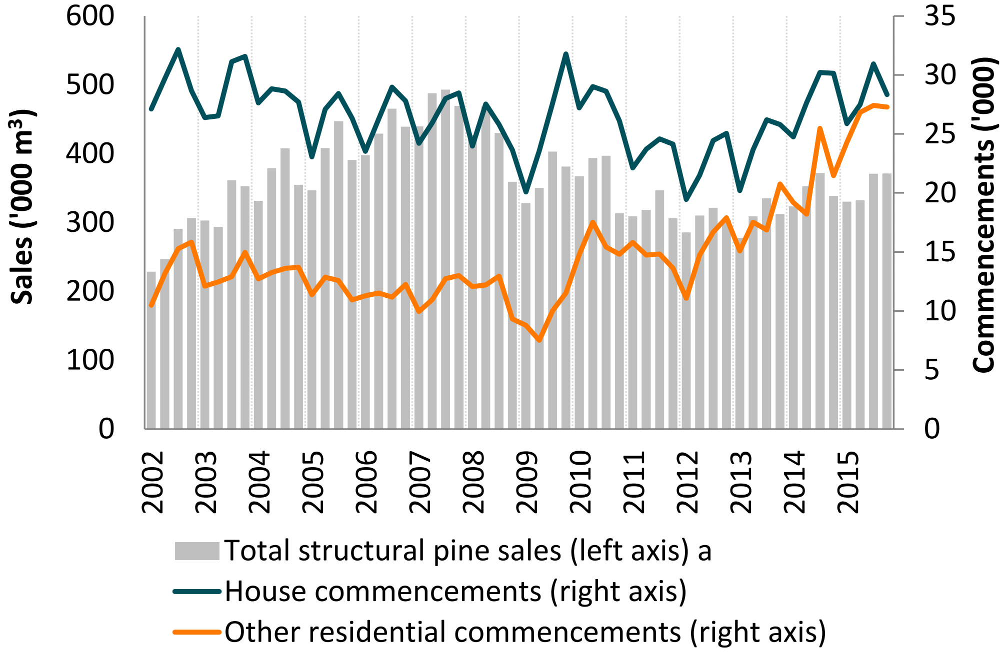
Figure 3 House commencements and quarter-on-quarter change in sales of selected wood products, March quarter 2002 to December quarter 2015



Note: Observations for treated pine range from March 2005 to December 2015. Observations for all other series range from March 2002 to December 2015.
Sources: ABS 2016b; FWPA Softwood data series

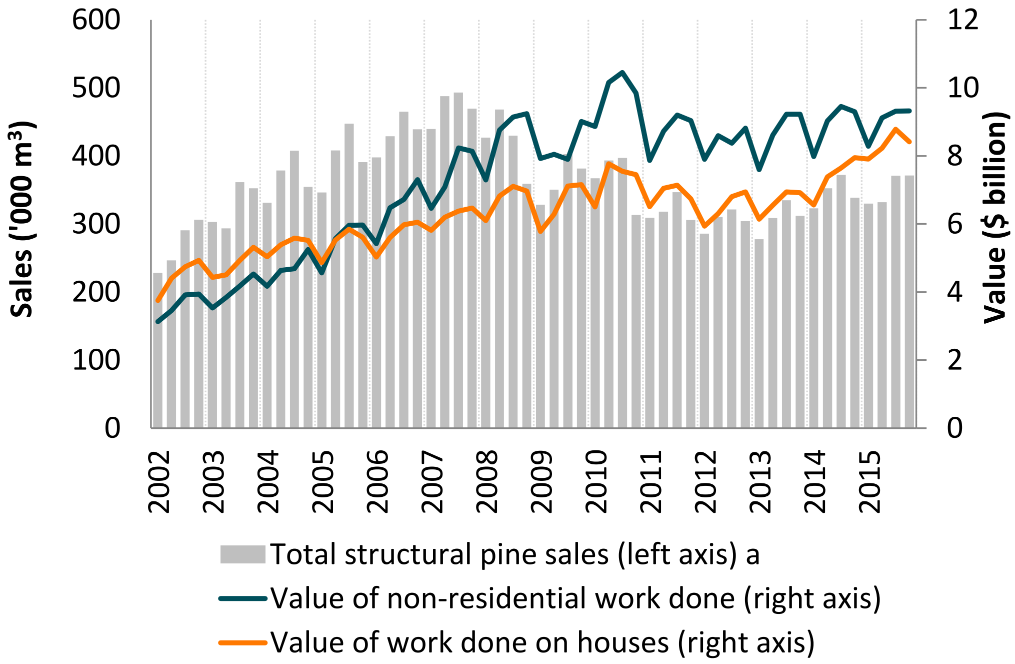
The disparity between structural timber sales and dwelling commencements may be explained by increases in the value of work done on houses, and non-residential work done, from 2002 to 2007 (Figure 5). However, increases in values may not reflect increases in activity and the volume of wood used in non-residential construction is relatively small, with other material such as steel and concrete dominating. Nevertheless, these series along with the value of alterations and additions, are still included as possible explanatory variables for completeness.

Figure 4 Dwelling commencements and quarterly sales of structural pine, March quarter 2002 to December quarter 2015



a Only includes sales in the FWPA Softwood data series.
Sources: ABS 2016c; FWPA Softwood data series

Figure 5 Value of residential and non-residential building and quarterly sales of structural pine, March quarter 2002 to December quarter 2015

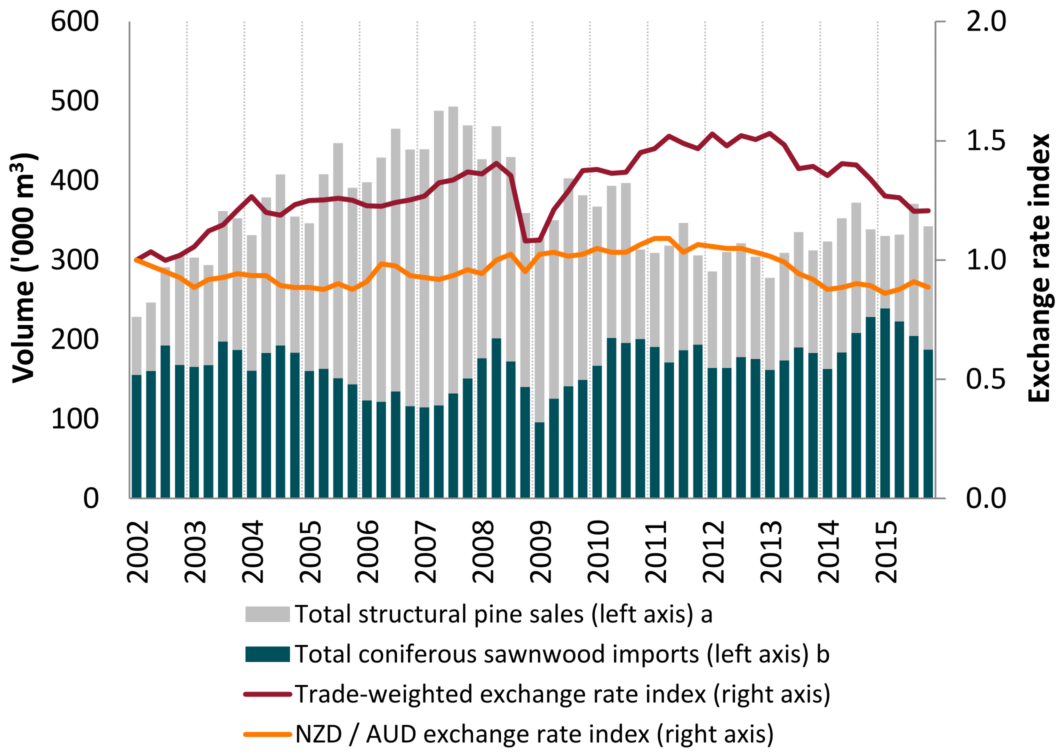


a Only includes sales in the FWPA Softwood data series.
Sources: ABS 2016b; FWPA Softwood data series

Another reason for increased sales from 2002 to 2007 may be changes in the number of producers included in the FWPA Softwood data series. Increases in the number of producers over the sample period may result in an upward trend in the series even if total industry sales remained constant over the same period (see [Discussion and limitations] for further information).

Medium-term trends in the FWPA Softwood data series may also be explained by changes in imports of similar products. The decrease in total softwood sawnwood imports from March 2004 to December 2006 may explain some of the increase in total structural pine sales from Australian sawmills over the period (Figure 6). A key factor affecting substitution of imports is the Australian dollar against the currencies of major trading partners. Appreciation of the Australian dollar is likely to drive substitution of imports for domestic sales, resulting in an observed decrease in sales.

Figure 6 Trade series and quarterly sales of structural pine, March quarter 2002 to December quarter 2015



a Only includes sales in the FWPA Softwood data series. **b** Industry total.
Source: ABS 2016a; FWPA Softwood data series

Stochastic trends and cointegration (technical)

Stochastic trends

Like many economic series, the four wood product sales series appear to be non-stationary, containing trends that prevent them from fluctuating around the same level of sales over the long-run. This trend may be deterministic in nature, where sales increase or decrease over time in a predictable way, or random in nature, where sales tend to increase or decrease randomly each period. These trends can also persist quarter to quarter and season to season.

Standard estimation procedures have been shown to be invalid in the presence of stochastic trends. To determine any transformation that must be applied prior to estimation, it is important to identify the type of trend underlying the series. Relationships can then be estimated more accurately.

The treated pine series was an exception to this trend, showing some evidence of an additional stochastic trend at the semi-annual frequency. This suggests that an appropriate approach to modelling the treated pine series may be to estimate equations describing the semi-annual change or growth rate in sales. Given the mixed evidence, ABARES has considered both approaches by estimating both types of models for treated pine sales.

Cointegration

With multiple series containing stochastic trends, two or more series may be cointegrated, sharing a common stochastic trend. Cointegrated variables can be modelled using an error correction form, where deviations from a long-run or steady state equilibrium can help to explain short-run movements in the series.

Table A2 and Table A3 in Appendix A present the results of formal tests for stochastic trends at various frequencies in the wood product sales series and important explanatory variables. The test results provided strong evidence of a stochastic trend at the quarterly frequency for all four sales series and many of the explanatory variables. This suggests that the most appropriate approach to modelling the sales series is to estimate equations describing the quarterly change or growth rate in sales as a function of the quarterly change or growth rate in explanatory variables. It also implies that sales in the current quarter are a strong predictor of sales in the next quarter.

Table A4 in Appendix A presents the results of formal tests for cointegration relationships between the three structural pine series and house commencements. The test results suggested evidence of cointegration between category 1 and category 2 untreated pine sales, and mixed evidence of cointegration between treated and untreated pine sales. To address this, ABARES estimated several error correction models (see Modelling framework for further information). The results of these models are presented in Appendix B.

3 Modelling framework

This study focused on producing accurate short-term forecasts. To do this ABARES estimated and tested a large number of models with varying degrees of complexity, functional forms and explanatory variables. ABARES then assessed the out-of-sample forecasting performance of these candidate models by comparing forecasts with actuals over a subset of the sample period. The preferred econometric models and combinations of models were chosen on the basis of their out-of-sample forecasting performance and ease of interpretation.

The models estimated in this report are not based on any formal structural economic models of the various wood product markets. The models are based on historical relationships between the sales series and various explanatory variables. The models are not intended to explicitly model the functioning of the various wood product markets. However, they do generate predictions of future sales, assuming that past relationships persist into the future.

Econometric models

Across the four wood product sales series nine different econometric models were estimated, including five models of individual sales series, two models of the ratio of two series and two vector error correction models (Table 2). Detailed results and explanations of these models are in Appendix B. Various combinations of these nine models were used to generate unique forecasts of the four sales series (see Selecting the preferred combination of models).

Models of individual sales series included models of landscape wood products, treated pine and category 1 untreated pine sales (LNDSCP, TREAT and CAT1) as well as models of total structural pine (STRUCT) and total untreated pine sales (UNTREAT). Models of the ratio of two series included a model of the share of treated pine sales as a proportion of total structural pine sales (RATIO_STRUC), and a model of the share of category 2 sales as a proportion of total untreated pine sales (RATIO_UNTREAT). The two vector error correction models comprised a model relating sales of total untreated pine and treated pine to one another (VEC_STRUCT) and a model relating category 1 and category 2 sales to one another (VEC_UNTREAT).

The three types of econometric models differ in complexity and the assumed degree of interaction between sales series. For example, models of individual sales series assume no interdependence between sales of various wood products. Models of the ratio of two series imply that changes in sales of one series can be related to changes in another series in a simple way. In contrast, vector error correction models assume that sales of multiple wood products can be related to one another through a steady-state relationship, where deviations from the steady-state relationship in one period help to explain short-run movements in the series in the following period.

No single equation models of category 2 sales were considered appropriate for forecasting because of poor in-sample performance. Landscape wood products sales were estimated using only single equation models, reflecting an assumption that sales of landscape wood products are independent of sales of structural pine.

Table 2 Econometric models used in this study

Econometric model	Description	Estimated equation
LNDSCP	Model of landscape wood products sales	$\Delta ln(lndscp_t) = 0.14 - 0.22*d_1 - 0.14*d_2 - 0.09*d_3 - 0.41*\Delta ln(lndscp_{t-1}) - 0.20*\Delta ln(lndscp_{t-2}) - 0.19*\Delta ln(lndscp_{t-3})$ **a**
TREAT	Model of treated pine sales	$\Delta treat_t = - 5424 + 15075*d_1 + 5764*d_2 + 10428*d_3 + 2.68*\Delta hc_t$ **a**
CAT1	Model of category 1 untreated pine sales	$\Delta ln(cat1_t) = - 0.10 + 0.16*d_1 + 0.11*d_2 + 0.13*d_3 + 0.66*\Delta ln(hc_t)$ **a**
STRUCT	Model of total structural pine sales	$\Delta_2 ln(struct_t) = - 0.18 +0.16*d_1 + 0.34*d_2 - 0.21*d_3 - 0.59*\Delta_2 ln(struct_{t-1})$
UNTREAT	Model of total untreated pine sales	$\Delta ln(untreat_t) = - 0.06 +0.15*d_1 + 0.11*d_2 - 0.11*d_3 - 0.001*trend + 0.60*\Delta ln(hc_t) + 0.10*\Delta ln(oc_t) - 0.50*\Delta ln(er\_nz_t)$
RATIO_STRUC	Model of the share of treated pine sales as a proportion of total structural pine sales	$\Delta treat\_share_t = 0.008$
RATIO_UNTREAT	Model of the share of category 2 sales as a proportion of total untreated pine sales	$\Delta cat2\_share_t = - 0.63*model\_error_{t-1}$ **a**
VEC_STRUCT	Vector error correction model of category 1 and category 2 untreated pine sales	$\Delta ln(untreat_t) = - 0.11 + 0.16*d_1 + 0.13*d_2 + 0.11*d_3 + 0.54*\Delta ln(hc_t) - 0.47*\Delta ln(er\_nz_t) + 0.01*LR_{t-1}$ $\Delta ln(treat_t) = - 0.04 + 0.15*d_1 + 0.08*d_2 + 0.15*d_3 + 0.70*\Delta ln(hc_t) - 0.04*\Delta ln(er\_nz_t) + 0.11*LR_{t-1}$ $LR_{t-1} = ln(untreat_{t-1}) - 2.70*ln(treat_{t-1}) + 15.85 + 0.05*trend$
VEC_UNTREAT	Vector error correction model of treated and total untreated pine sales	$\Delta ln(cat1_t) = - 0.11 + 0.16*d_1 + 0.12*d_2 + 0.10*d_3 + 0.64*\Delta ln(hc_t) + 0.11*LR_{t-1}$ $\Delta ln(cat2_t) = - 0.08 + 0.13*d_1 + 0.13*d_2 + 0.12*d_3 + 0.47*\Delta ln(hc_t) + 0.64*LR_{t-1}$ $LR_{t-1} = ln(cat1_{t-1}) - 0.88*ln(cat2_{t-1}) + 3.38$

Note: Results in this table are for the period March 2002 to December 2012. **a** Coefficient estimates for these models differ from those of the most up-to-date version presented in Section 4. Detailed results, variable descriptions and sources are in Appendix B.

Identifying candidate models

In developing the nine econometric models shown in Table 2, over 40 candidate models with suitable in-sample properties were estimated with various functional forms and combinations of explanatory variables (detailed results for the candidate models can be found in Appendix B).

In searching for candidate models, ABARES gave preference to models with fewer variables and simpler dynamics. Smaller and simpler models have fewer data requirements, are easier to explain and tend to have better out-of-sample forecasting performances. Smaller models also have an advantage when using smaller data sets because each additional variable reduces the effective sample size and increases the uncertainty around model estimates.

The model specification procedure considered deterministic terms, such as seasonal dummies and trends, and time series processes, such as auto-regressive and moving average processes. The procedure also considered exogenous explanatory variables, including:

- past sales
- house and other residential commencements
- value of alterations and additions, work done on houses and non-residential construction activity
- Australian dollar against major trading partners' currencies (euro, US dollar, NZ dollar and Japanese yen)
- sawmill input price index
- road transport price index
- gross domestic product (GDP)
- interest rates.

Models were considered to have acceptable in-sample properties if the estimated coefficients had the expected sign, and if assumptions required for consistent coefficient and variance estimates appeared to be met with an acceptable level of probability (meaning that the estimates were statistically robust). Appendix A provides details about the diagnostic tests used to assess statistical robustness.

In all cases, diagnostic tests were used to determine whether prerequisite assumptions for efficient estimation and valid inference were met in the candidate models. For example, least squares estimates are inefficient and inference invalid when residuals exhibit heteroscedasticity or autocorrelation. Furthermore, estimates are biased when models are incorrectly specified or explanatory variables are endogenous.

ABARES conducted residual diagnostic tests for autocorrelation, including the Breusch-Godfrey LM test (Breusch 1978; Godfrey 1978) and Ljung-Box Q-statistics (Ljung & Box 1978), and diagnostic tests for heteroscedasticity, including the Breusch-Pagan-Godfrey test (Breusch & Pagan 1979; Godfrey 1978) and White test (White 1980). The Ramsey RESET test (Ramsey 1969), was used to simultaneously test for inappropriate transformations of the dependent variable, endogenous regressors and incorrect functional form. Influential observations and outliers were identified using Studentised residuals and DFFITS (Belsley, Kuh & Welsh 1980). Finally, the presence of structural breaks at specified dates was tested using the Chow breakpoint test (Chow 1960). However, given the small sample size, little could be done about significant structural breaks.

Validating out-of-sample forecasting performance

To evaluate the likely out-of-sample forecasting performance of the 43 candidate models, the dataset was divided into two periods: a training period (from March 2002 to December 2012), over which the models were initially estimated, and a validation period (from March 2013 to December 2015), over which forecasts were compared with actual sales.

In generating forecasts over the validation period, the model coefficients were updated every quarter with the latest available data to generate a new set of four-quarters-ahead forecasts. In this way the validation exercise mimics the actual procedure used to generate rolling four-quarters-ahead forecasts for FWPA. However, it differs in that the forecasts over the validation period are based on the actual values of exogenous variables rather than on forecasts. As a result, the estimated out-of-sample forecasting properties of the candidate models are consistent with what would be seen in practice if the explanatory variables had been forecasted with 100 per cent accuracy. While this approach is likely to overestimate the apparent accuracy of the models, it allows the model selection process to be undertaken independently of any external forecasts used in the final models.

In assessing the out-of-sample forecasting performance of the models, ABARES considered both point and directional forecasting accuracy. Point accuracy refers to the distance between forecasts and actual sales. Directional accuracy refers to the rate of success in predicting whether sales move up or down relative to the previous quarter. The primary error measure used to estimate point forecast accuracy was the root mean squared error (RMSE) (Greene 2003). The RMSE measure is preferred because it applies exponential weighting to forecast errors based on their size. It therefore applies a relatively more severe penalty to models that may generate large forecast errors for specific observations. However, mean absolute percentage errors (MAPE) are also presented for convenience of interpretation. Directional forecasting accuracy was estimated by counting the proportion of sales movements that were correctly predicted over the validation period.

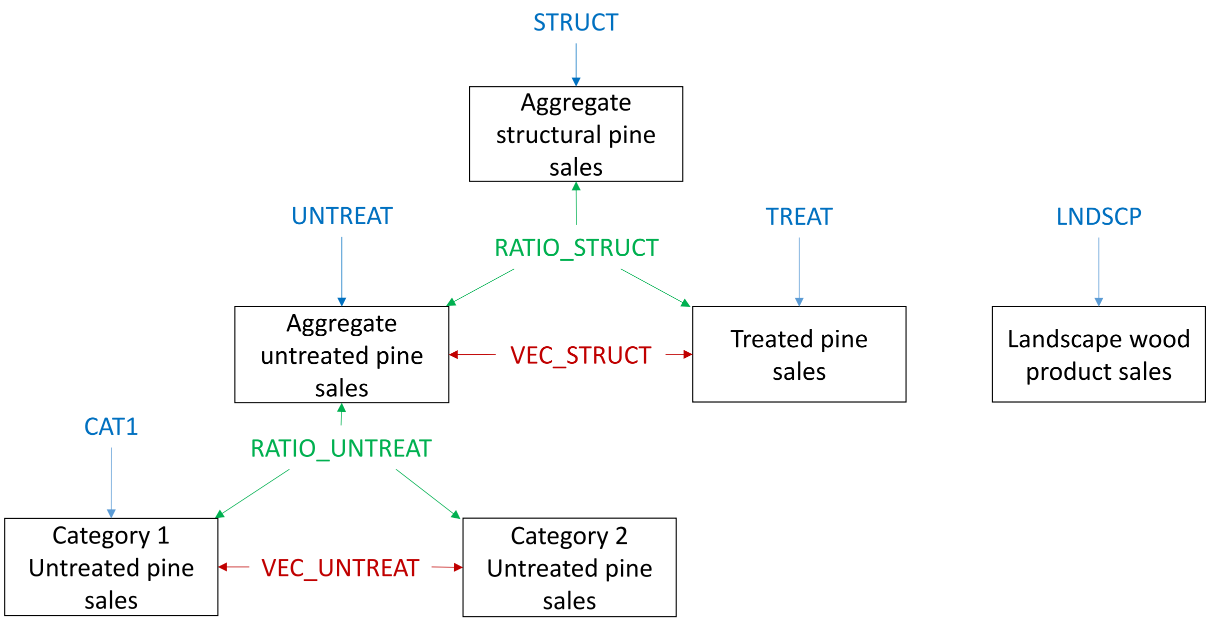
Over the validation period there were 11 one-quarter-ahead forecasts, 10 two-quarters-ahead forecasts, nine three-quarters-ahead forecasts and eight four-quarters-ahead forecasts. There were eight complete sets of four-quarters-ahead forecasts and therefore eight forecasts of total sales over the coming year. For the same model, forecasting accuracy and directional accuracy varied across time horizons, making it necessary to calculate an average point forecasting error and directional accuracy. This was done by calculating the average forecasting accuracy and directional accuracy over the validation period using the eight sets of four-quarters-ahead forecasts. Consequently, the average point and directional forecasting errors exclude the last three one-quarter-ahead forecasts, last two two-quarters-ahead forecasts and the last three-quarters-ahead forecast in the validation period. Estimates of the point forecasting accuracy and directional accuracy of all candidate models are presented in Appendix B.

In many cases, there was no candidate model suitable for all contexts. Different models generated more accurate forecasts over different time horizons—and sometimes the model that produced the most accurate point forecasts did not produce the most reliable predictions of the direction of sales. Where it was unclear which model should be chosen, preference was given to point forecasting accuracy rather than directional accuracy. Simpler models that had better overall point forecasting accuracy were also preferred over more complex models or models that predicted a specific time horizon with great accuracy.

Selecting the preferred combination of models

After identifying the preferred econometric models shown in Table 2, various subsets of the nine econometrics models were combined to generate forecasts of the four sales series. Of the large number of potential model combinations illustrated in Figure 7, only the 18 combinations that generated a single forecast for each of the four sales series were considered. In the interests of internal consistency, all other combinations of models were excluded because they generated multiple forecasts of one or more of the series.

Figure 7 Relationship between econometric models and sales series



Note: Shows the nine types of econometric models estimated in this study as described in Table 2.
Source: ABARES

Table 3 shows which of the nine econometric models are included in each of the 18 combinations of models. Use of 'Yes' indicates that a model is included in a particular combination. For example, the first combination of models combines the preferred model for landscape wood products sales (LNDSCP), treated pine sales (TREAT), category 1 untreated pine sales (CAT1), and total untreated pine sales (UNTREAT). Table C1 in Appendix C provides details around the calculations used to generate forecasts for each of the sales series using the various combinations of models.

The out-of-sample forecasting performance of various combinations of the models were assessed using the same validation procedure used to pare down the candidate models. However, in comparing the out-of-sample forecasting performance of combinations of models, the average RMSE and directional forecasting accuracy across all four series was used. Estimates of the point forecasting accuracy and directional accuracy for the various combinations of models are presented in Appendix C.

Based on the out-of-sample forecasting performance of the nine econometric models, the preferred combination of models (combination 3) was comprised of models of landscape wood products sales (LNDSCP), treated pine sales (TREAT), category 1 untreated pine sales (CAT1) and a model of the share of category 2 sales as a proportion of total untreated pine sales (RATIO_UNTREAT).

Table 3 Combinations of econometric models considered in this study

Model	**Combinations of econometric models**																	
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
LANDSCP	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TREAT	Yes	Yes	Yes	Yes	Yes	Yes	Yes	–	–	–	–	–	–	–	–	–	–	–
CAT1	Yes	Yes	Yes	–	–	–	–	–	–	–	Yes	Yes	Yes	Yes	Yes	–	–	–
STRUCT	–	Yes	–	Yes	–	–	–	Yes	–	–	Yes	–	Yes	–	–	Yes	Yes	–
UNTREAT	Yes	–	–	–	–	–	Yes	Yes	Yes		Yes	Yes	–	–	–	–	–	–
RATIO_STRUCT	–	–	–	–	Yes	–	–	–	Yes	–	–	Yes	Yes	Yes	–	Yes	–	Yes
RATIO_UNTREAT	–	–	Yes	Yes	Yes	–	Yes	Yes	Yes	Yes	–	–	–	Yes	–	Yes	–	–
VEC_STRUCT	–	–	–	–	–	Yes	–	–	–	–	–	–	–	–	–	–	Yes	Yes
VEC_UNTREAT	–	–	–	–	–	–	–	–	–	Yes	–	–	–	–	Yes	–	–	–

Note: Models are as described in Table 2. 'Yes' indicates that the econometric model is included in a particular combination of models. Table C1 in Appendix C shows how forecasts for from various econometric models are combined to generate forecasts for each of the four wood product sales series.

4 Forecasting equations and errors

This section presents the preferred model equations used for forecasting the four wood product sales series along with measures of out-of-sample forecasting performance. The model selection process involved comparing models estimated over the training period (March 2002 to December 2012). The equations presented in this section were estimated over the entire sample period (March quarter 2002 to December quarter 2015) and, therefore, represent the most up-to-date version of the models.

The forecast errors presented here assume that the future value of exogenous drivers included in the equations are known with certainty. In practice, uncertainty around these preliminary forecasts will add to uncertainty around the ABARES forecasts.

The models describe the expected changes in the series as a function of past changes, exogenous drivers and seasonal effects. In order to generate four-quarters-ahead forecasts, the models are run recursively, using previously forecasted values of the series and forecasts of exogenous drivers over the forecasting period.

While many factors were hypothesised by ABARES to affect wood product sales, most of these are not included in the final models. This is because they were either found to be statistically insignificant or their inclusion resulted in less accurate out-of-sample forecasts.

Variables found to be statistically insignificant included GDP, interest rates, exchange rates, the value of residential alterations and additions, non-residential construction activity and the value of work done on houses. In many cases, the statistical insignificance of these variables was likely the result of a high degree of correlation with variables already included in the models (such as house commencements), making estimation of their impact on sales more uncertain.

A number of variables were statistically significant but did not improve out-of-sample forecasting performance of the estimated models. In particular, the NZ/Australian dollar exchange rate, other residential commencements, sawmill input costs and road transport costs were found to have statistically significant explanatory power over the historic sales series, but their inclusion resulted in less accurate forecasts over the validation period.

Landscape wood products

Model estimates and interpretation

Preliminary tests (outlined in Appendix A) suggested that the most appropriate approach to modelling the volume of sales of landscape wood products was to estimate the quarterly change or growth rate in sales (see Table A2, Appendix A). Through the model specification process, four single equation models were identified as having suitable in-sample properties. Detailed results for all candidate models of landscape wood products sales are summarised in Table B2 and Table B3 in Appendix B.

The preferred model for sales of landscape wood products is a pure time series model that estimates quarterly growth in sales as a function of past growth and seasonal effects. Equation 1 shows the estimated model and parameters based on data up to and including December 2015.

Equation 1:

$$\Delta ln(lndscp_t) = 0.13 - 0.25*d_1 - 0.11*d_2 - 0.08*d_3 - 0.33*\Delta ln(lndscp_{t-1}) - 0.14*\Delta ln(lndscp_{t-2}) - 0.20*\Delta ln(lndscp_{t-3})$$

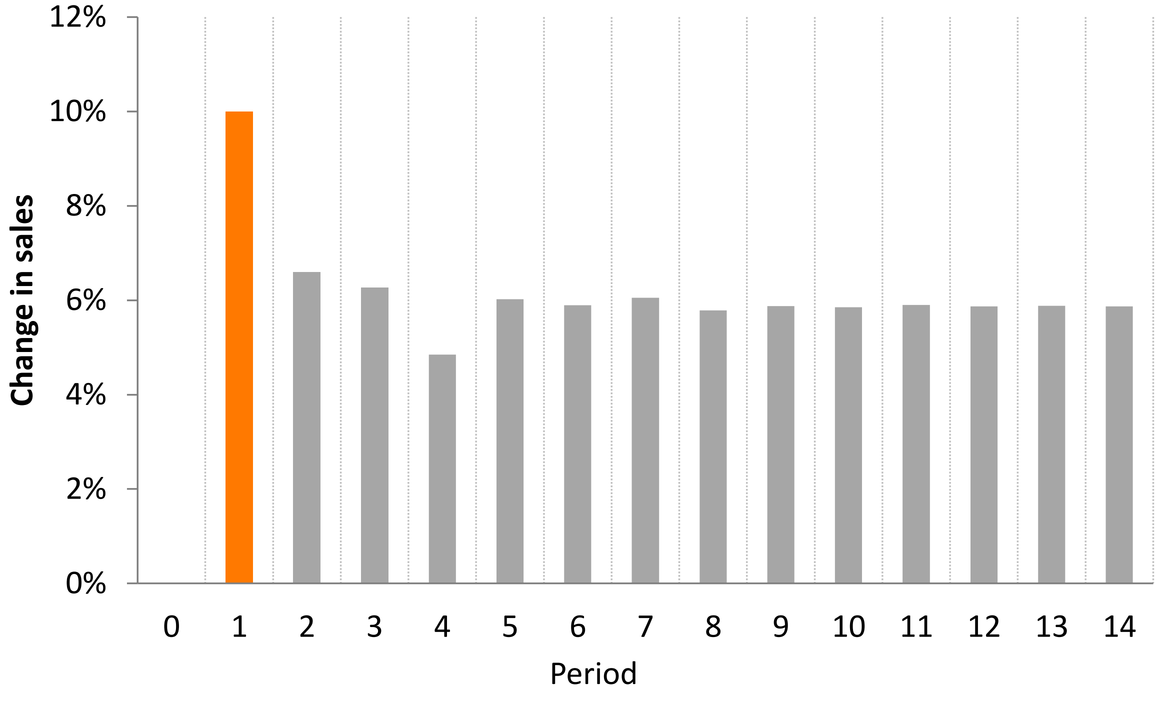
where:

$\Delta ln(lndscp_t)$ is the quarterly change in the natural logarithm of landscape wood products sales at time t

d_1, d_2 and d_3 are seasonal dummy variables for the March, June and September quarters, respectively.

The estimated model implies that the expected growth rates in sales next quarter indirectly depends on growth in all previous quarters. An initial increase in sales is partially but not fully offset in future quarters (Figure 8) with the effects of a one-time shock to sales having a permanent impact on the level of sales. For example, if sales next quarter are 10 per cent higher than otherwise, then sales in the following quarter will be approximately 6.5 per cent higher, and sales in the subsequent quarter will be 6.3 per cent higher than otherwise. In the absence of any further unexpected changes to sales, the long-term level of sales will be around 5.9 per cent higher than otherwise, indicating that unexpected shocks have a permanent effect on sales.

Figure 8 Landscape wood products, long-term impact of unexpected increase in sales



Note: Periods represent quarters. Shows the effects of a 10 per cent increase in sales in period 1 on the level of sales in future periods, measured relative to the level of sales in period 0.
Source: ABARES estimates

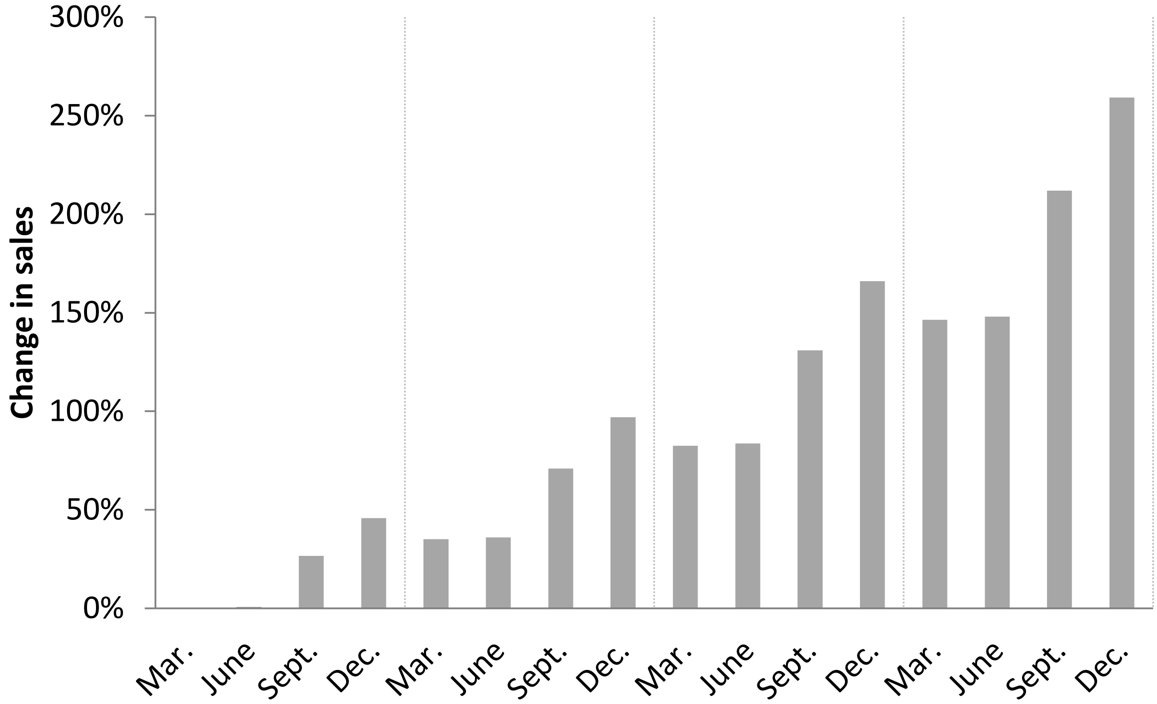
Constant and seasonal terms represent a unique scaling effect applied to sales in each quarter (Table 4) and imply that landscape sales are expected to increase over time, with short-term peaks in the December quarter of each year (Figure 9).

Table 4 Landscape wood products sales, trend and seasonal effects

Quarter	Growth in sales (%)
March	-7
June	+1
September	+26
December	+15

Source: ABARES estimates

Figure 9 Landscape wood products, impact of estimated trend and seasonal effects on future sales relative to base quarter



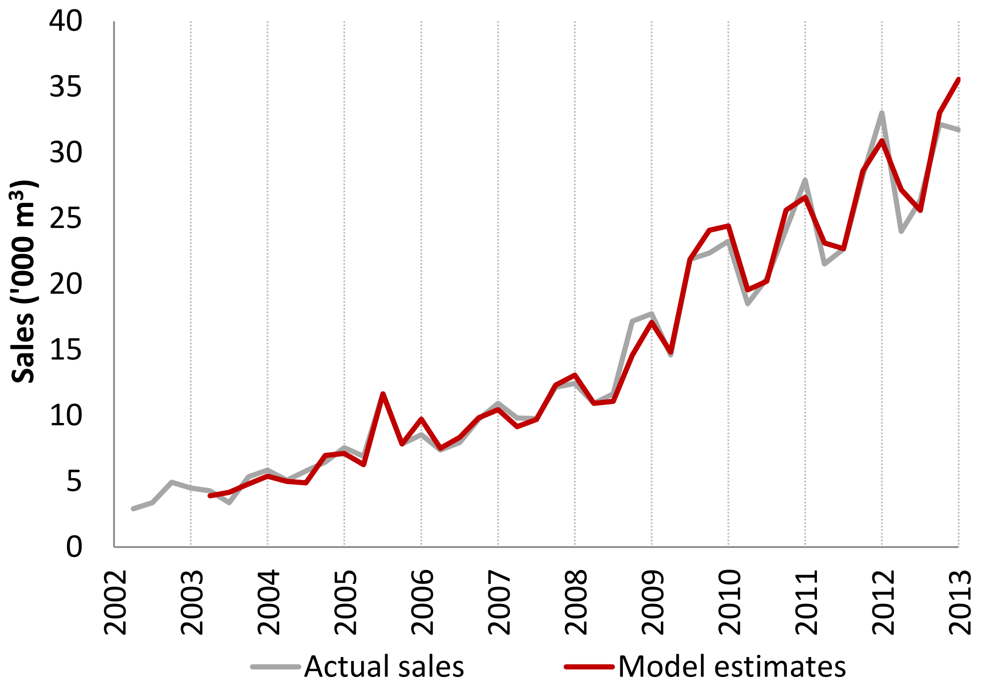
Note: Shows the effect of trend and seasonal terms on the level of sales in future periods, measured relative to the level of sales in the first quarter shown.
Source: ABARES estimates

Forecast evaluation

Figure 10 compares in-sample model estimates with actual sales over the training period (March quarter 2002 to December quarter 2012) while Figure 11 compares out-of-sample forecasts with actual sales over the validation period (March quarter 2013 to December quarter 2015). Associated forecast error measures and directional accuracy are summarised in Table 5.

Over the training period, the model appears to fit the historical data well (Figure 10), with estimates falling within 5.8 per cent of actual sales, on average. The model also appears to capture most of the turning points in the series, correctly predicting the direction of sales more than 87 per cent of the time.

Figure 10 Landscape wood products, historic sales and model estimates, March quarter 2002 to December quarter 2013



Note: The model estimate and actual sales are identical in June 2005 because an observational dummy was included.
Source: ABARES estimates; FWPA Softwood data series

In terms of out-of-sample forecasting accuracy, the model performed only moderately well (Figure 11), with a mean forecast error of 10.8 per cent for all rolling forecasts over the validation period (Table 5). As expected, forecasts were most accurate over the one-quarter time horizon, with a mean error of 13 per cent. One-year-ahead forecasts were more accurate than forecasts over any specific time horizon with a mean error of 10.7 per cent, implying that forecast errors tend to partially cancel out over multiple quarters.

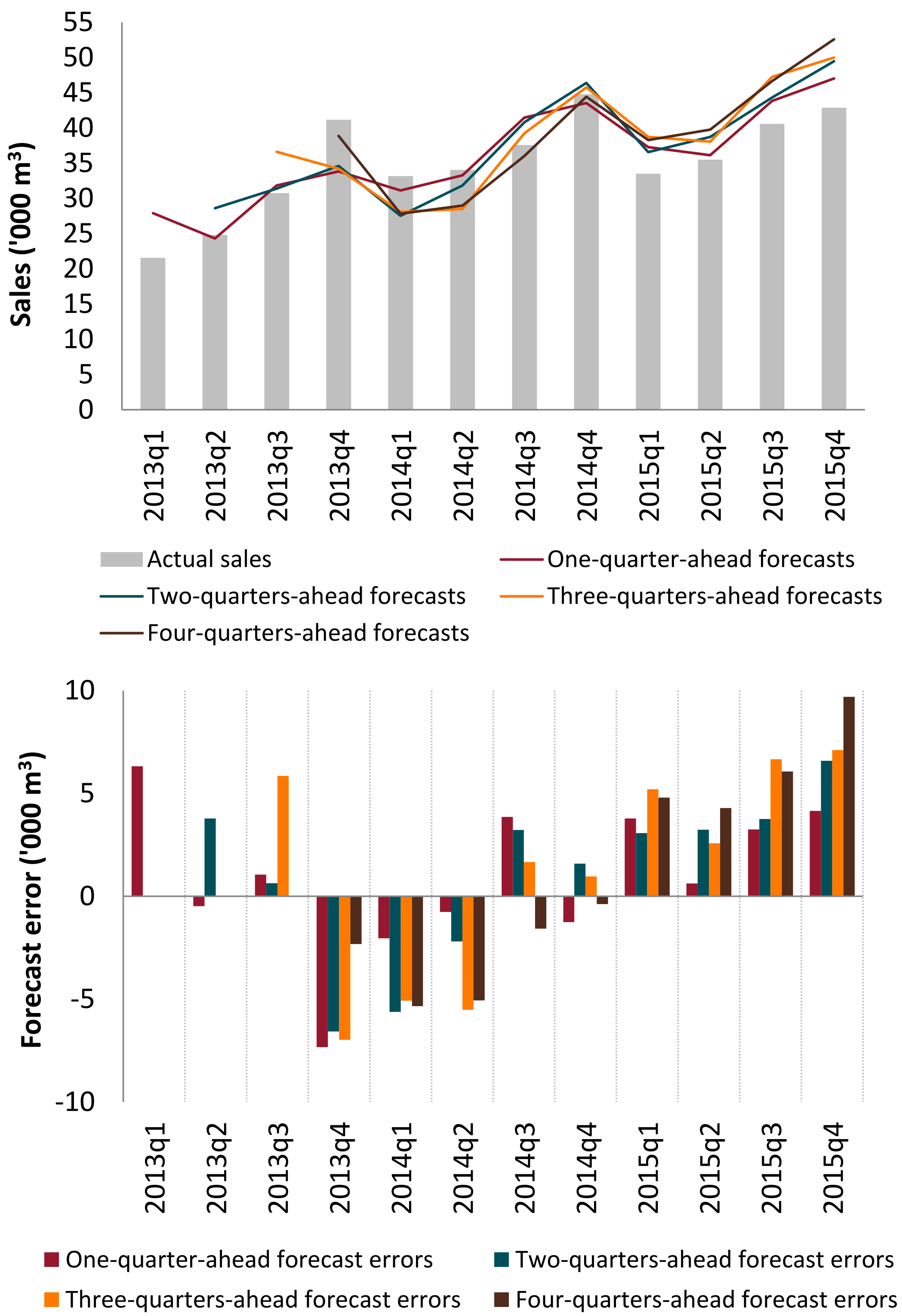
Table 5 Landscape wood products, out-of-sample forecasting performance

Time horizon	Point forecasting error (MAPE) (%)	Directional forecasting accuracy (%)
One-quarter-ahead	13.0	83
Two-quarters-ahead	13.9	100
Three-quarters-ahead	16.2	80
Four-quarters-ahead	13.2	100
Average **a**	10.9	91
Total sales over year ahead	10.7	100

a The average forecast error is based on the complete sets of four-quarters-ahead rolling forecasts. It excludes the last three one-quarter-ahead forecasts, last two two-quarters-ahead forecasts and last three-quarters-ahead forecasts. The average forecast error may be less than the horizon-specific forecast errors.
Source: ABARES estimates

While point forecasting accuracy was only moderate, the model predicted the direction of sales with a high degree of accuracy (Table 5). This can be seen in Figure 11, where forecasts tend to match the pattern of actual sales overall all four time horizons. On average, the direction of sales was correctly predicted more than 90 per cent of the time. While the model for landscape wood products sales may have limited use for point forecasting, it remains useful for predicting the direction of sales.

Figure 11 Landscape wood products, forecasts and actual sales, March quarter 2013 to December quarter 2015



Note: q1, q2, q3 and q4 refer to the March, June, September and December quarters, respectively.
Source: ABARES estimates; FWPA Softwood data series

Treated pine

Model estimates and interpretation

Preliminary tests (outlined in Appendix A) provided mixed evidence about the most appropriate way to model the treated pine sales series (see Table A2, Appendix A). The first approach ABARES considered was to model the quarterly change or growth rate in sales. The second approach was to model the semi-annual change or growth rate in sales.

Through the model specification process, four single equation models were identified as having suitable in-sample properties. Detailed results for all candidate models of treated pine sales are summarised in Table B4 and Table B5 in Appendix B.

Of the candidate models, the best model for forecasting treated pine was found to be a single equation model that considered changes in house commencements and seasonal effects. Equation 2 shows the estimated model and parameters based on data up to and including December 2015.

Equation 2:

$$\Delta treat_t = -3549 + 12441 * d_1 + 3930 * d_2 + 9520 * d_3 + 2.59 * \Delta hc_t$$

where:

$\Delta treat_t$ is the quarterly change in treated pine sales at time t

d_1, d_2 and d_3 are seasonal dummy variables for the March, June and September quarters, respectively

Δhc_t is the quarterly change in house commencements at time t.

The estimated coefficients of the model imply that the volume of sales next quarter is positively correlated with the expected change in house commencements, with each additional house commencement expected to increase sales of treated pine by 2.59 cubic metres. This estimate is far below the actual amount of softwood timber used in the average detached dwelling (Kapambwe et al. 2008) because most wood used in housing construction is untreated pine. Furthermore, the estimate does not include the long-term increases in treated pine use per dwelling captured by the estimated seasonal effects (Table 6).

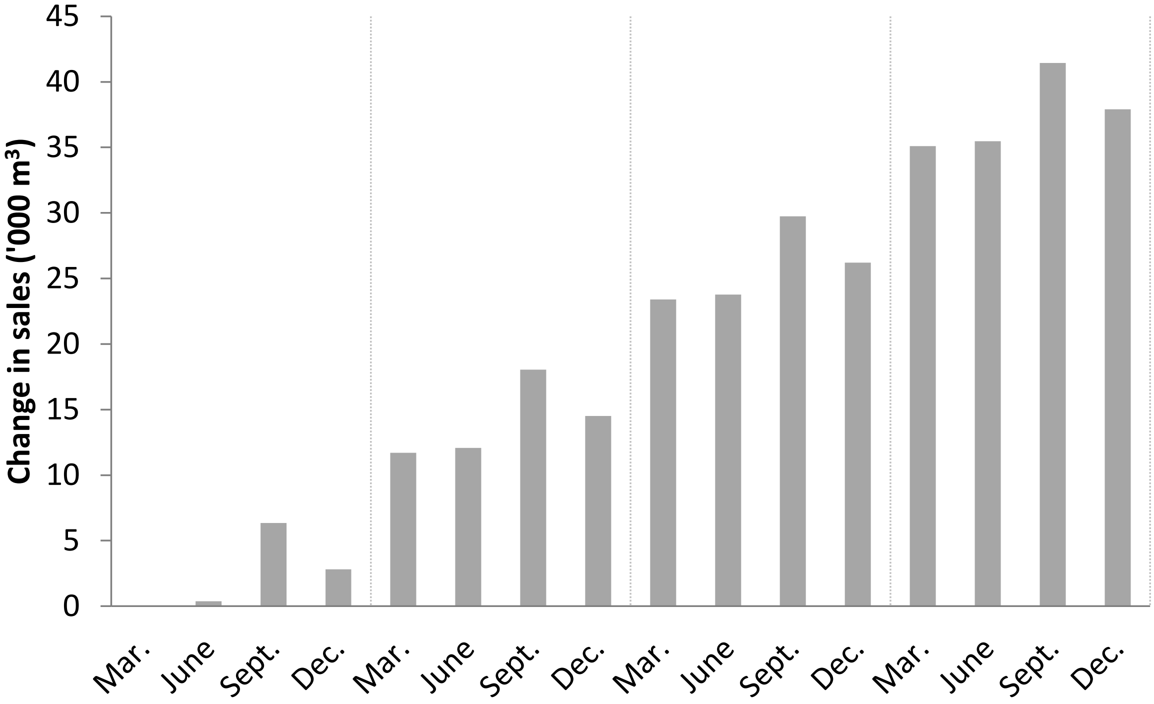
Table 6 Treated pine, trend and seasonal effects

Quarter	Change in sales ('000 m^3)
March	+8 893
June	+382
September	+5 972
December	-3 548

Source: ABARES estimates

The estimated constant and seasonal effects imply that, holding house commencements constant, sales will tend to increase over time (by around 22 000 cubic metres a year) with short-term peaks in the September quarter of each year (Figure 12). This long-term upward trend in treated pine use per dwelling could reflect substitution of treated pine for other products traditionally used in house construction.

Figure 12 Treated pine, impact of estimated trend seasonal effects on future sales



Note: Shows the effect of trend and seasonal terms on the level of sales in future periods, measured as the difference between sales in the current period and sales in the first quarter shown.
Source: ABARES estimates

Forecast evaluation

Figure 13 compares model estimates with actual sales over the training period (March quarter 2002 to December quarter 2012) and Figure 14 compares forecasts with actual sales over the validation period (March quarter 2013 to December quarter 2015). Associated forecast error measures and directional accuracy are summarised in Table 7.

Over the training period, the model fits the data well (Figure 13), with estimates falling within 6.1 per cent of actual sales, on average. The model also appears to capture most of the turning points in the series, correctly predicting the direction of sales more than 86 per cent of the time.

In terms of out-of-sample forecasting accuracy, the model performed very well over the validation period (Figure 14) but showed a tendency to under predict sales in the December quarter. Taking into account all rolling forecasts over the validation period, the model predicted actual sales with a mean error of 3.2 per cent (Table 7). As expected, one-quarter-ahead forecasts were the most accurate with a mean error of 4.5 per cent, and four-quarters-ahead forecasts were the least accurate, with a mean error of 5.8 per cent. Total sales over the year ahead were predicted with a mean error of only 3.2 per cent, implying that that forecast errors tend to cancel out over the medium term.

Figure 13 Treated pine, historic sales and model estimates, March quarter 2005 to December quarter 2013

Source: ABARES estimates; FWPA Softwood data series

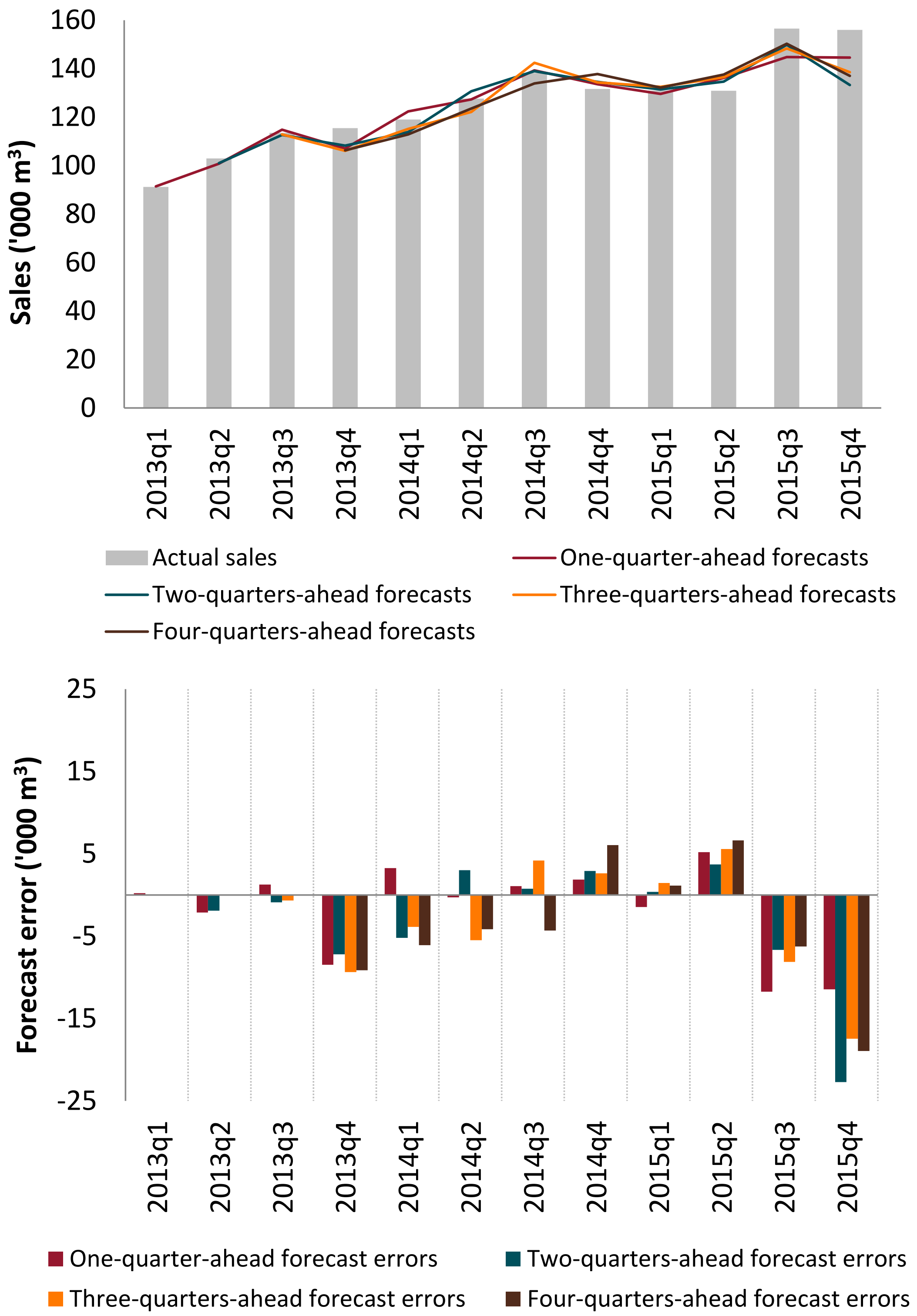
Table 7 Treated pine, out-of-sample forecasting performance

Time horizon	Point forecasting error (MAPE) (%)	Directional forecasting accuracy (%)
One-quarter-ahead	4.5	82
Two-quarters-ahead	5.0	82
Three-quarters-ahead	5.4	60
Four-quarters-ahead	5.8	67
Average **a**	3.2	73
Total sales over year ahead	3.2	100

a The average forecast error is based on the complete sets of four-quarters-ahead rolling forecasts. It excludes the last three one-quarter-ahead forecasts, last two two-quarters-ahead forecasts and last three-quarters-ahead forecasts. The average forecast error may be less than the horizon-specific forecast errors.
Source: ABARES estimates

The model also predicted the direction of sales over the validation period with a moderate to high degree of accuracy (Table 7). On average, the direction of sales was correctly predicted 73 per cent of the time over the validation period. As expected, accuracy was greater over one and two quarters (82 per cent) than over three and four quarters (60 and 67 per cent, respectively).

Figure 14 Treated pine, forecasts and actual sales March quarter 2013 to December quarter 2015



Note: q1, q2, q3 and q4 refer to the March, June, September and December quarters, respectively.
Source: ABARES estimates; FWPA Softwood data series

Category 1 and category 2 untreated pine

Model estimates and interpretation

Preliminary tests (outlined in Appendix A) suggested that the most appropriate approach to model sales of category 1 untreated pine was to estimate the quarterly change or growth rate in sales (see Table A2, Appendix A). Similarly, the most appropriate way to model the share of category 2 sales in total untreated pine was to estimate the quarterly change in share (see Table A2, Appendix A). With only two categories of untreated pine, estimating the share of one immediately gives the share of the other category.

Through the model specification process, five single equation models of category 1 untreated pine were identified as having suitable in-sample properties. Detailed results for all candidate models of category 1 untreated pine sales are summarised in Table B6 and Table B7 in Appendix B. Of the candidate models, ABARES found that the preferred model for forecasting was a simple model that considered growth in house commencements and seasonal effects. Equation 3 shows the estimated model and parameters based on data up to and including December 2015.

Through the model specification process, two single equation models of the share of category 2 untreated pine sales, as a proportion of total untreated pine sales, were identified as having suitable in-sample properties. Detailed results for all candidate models of category 2 untreated pine sales are summarised in Table B14 and Table B15 in Appendix B. Of the two candidate models, the preferred model was found to be a simple moving average model where the expected change in share is based on the previous quarter's model error. Equation 4 shows the estimated model and parameters based on data up to and including December 2015.

Equation 3:

$$\Delta ln(cat1_t) = -0.11 + 0.16*d_1 + 0.11*d_2 + 0.12*d_3 + 0.66*\Delta ln(hc_t)$$

Equation 4:

$$\Delta cat2\_share_t = -0.59*model\_error_{t-1}$$

where:

$\Delta ln(cat1_t)$ is the quarterly change in the natural logarithm of category 1 untreated pine sales at time t

d_1, d_2 *and* d_3 are seasonal dummy variables for the March, June and September quarters, respectively

$\Delta ln(hc_t)$ is the quarterly change in the natural logarithm of house commencements at time t

$\Delta cat2\_share_t$ is the quarterly change in the share of category 2 sales, as a proportion of total untreated pine sales, at time t

$model\_error_t$ is the difference between the predicted and actual share of category 2 sales at time t.

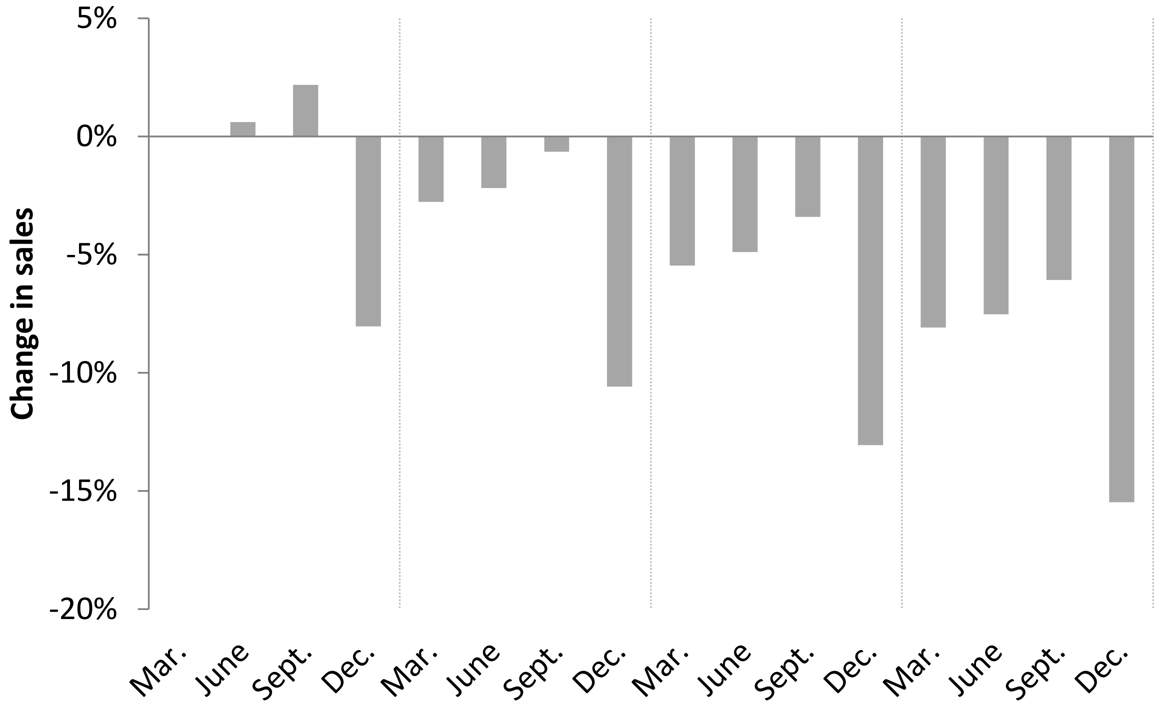
As anticipated, the expected volume of category 1 sales next quarter is positively correlated with the expected percentage change in house commencements (Equation 3). However, changes in sales are proportionally smaller than changes in house commencements, with a 1 per cent increase in house commencements expected to increase sales by 0.66 per cent. This implies that sales per dwelling change with the total number of house commencements—possibly as a result of substitution of other products (such as treated pine) for category 1 products, substitution of imports for domestically produced untreated pine or changes in the market share of the producers included in the data series over the sample period. Long-term decreases in sales per dwelling over time are captured in the constant and seasonal terms (Table 8). The estimated constant and seasonal terms imply that, holding house commencements constant, sales will decrease over time (by around 2.8 per cent a year) with short-term peaks in the September quarter of each year (Figure 15).

Table 8 Untreated pine, trend and seasonal effects

Quarter	Growth in sales (%)
March	+6
June	+1
September	+2
December	-10

Source: ABARES estimates

Figure 15 Category 1 Untreated pine, impact of estimated trend and seasonal effects on future sales

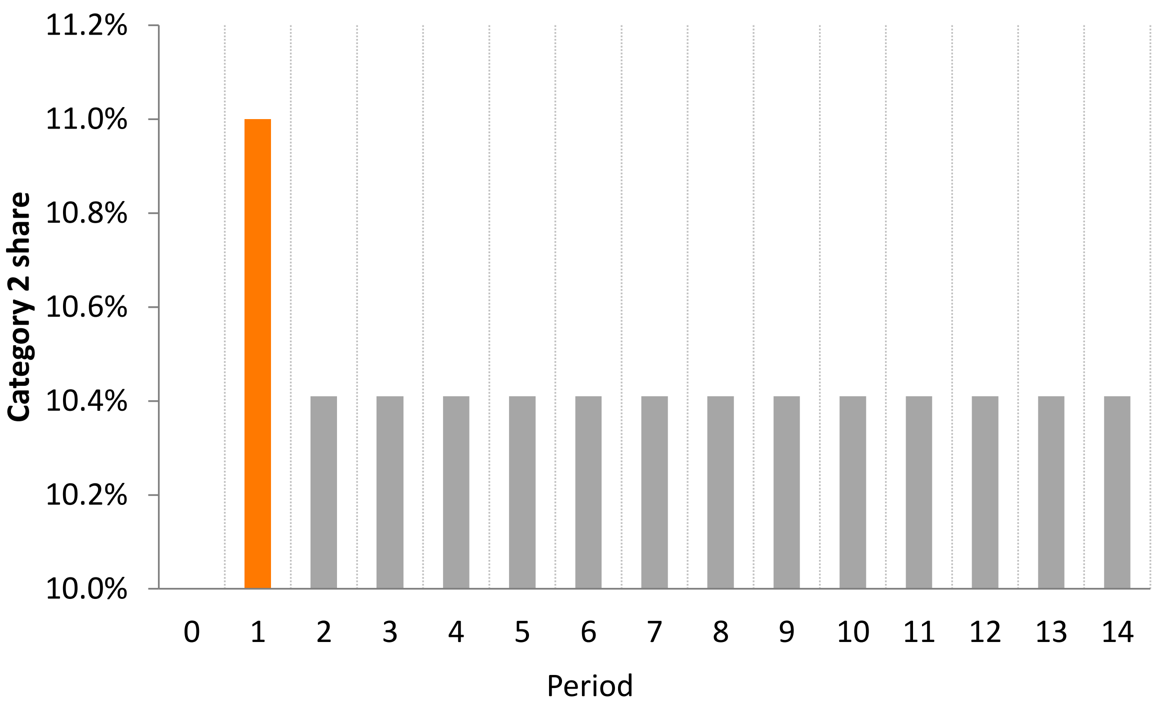


Note: Shows the effect of trend and seasonal terms on the level of sales in future periods, measured relative to the level of sales in the first quarter shown.
Source: ABARES estimates

In the absence of any changes in the share of category 2 sales as a proportion of total untreated pine sales, Equation 3 can also be used to model sales of category 2 untreated pine. However, in practice the share of category 2 sales as a proportion of total untreated pine sales is constantly changing (Equation 4). Equation 4 implies that the expected change in share of category 2 sales next quarter is zero plus an adjustment term for the unexpected change in the current quarter. Any unexpected change in the share of category 2 sales in the current quarter is partially reversed in the subsequent quarter. Part of any unexpected changes in the share of category 2 sales as a proportion of total untreated pine sales is permanent.

For example, an unexpected 1 per cent increase in the share of category 2 sales next quarter is expected to be followed by a decrease of 0.6 per cent in the following quarter (Figure 16). Without any further unexpected changes, the share of category 2 sales as a proportion of total untreated pine sales will remain constant at that level.

Figure 16 Category 2 Untreated pine, long term impacts of unexpected change in sales share



Note: Periods represent quarters. Shows the effects of a 1 per cent increase in the share of category 2 sales in period 1 on the share of category 2 sales in future periods, measured relative to the share at time 0.
Source: ABARES estimates

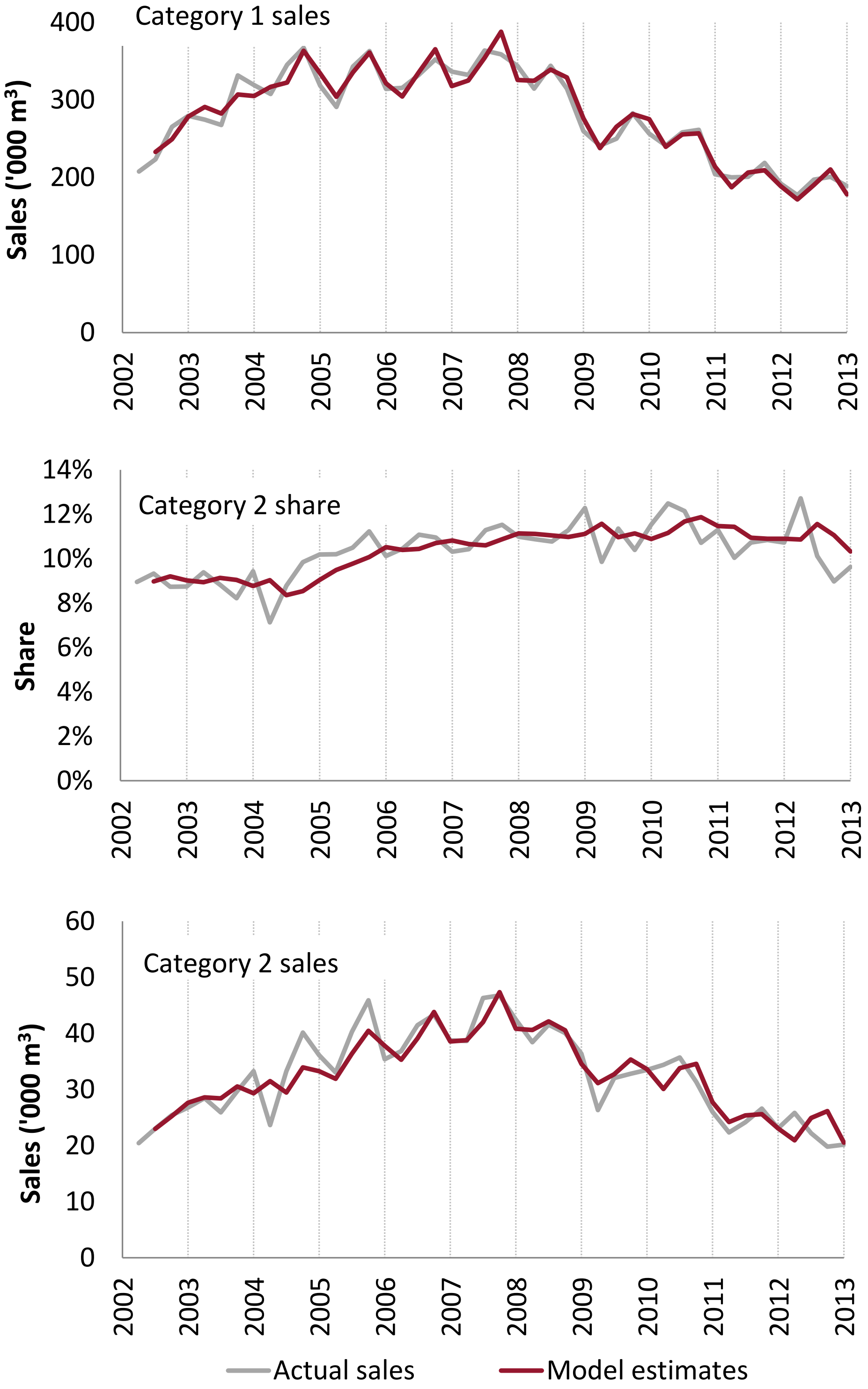
Forecast evaluation

Figure 17 compares model estimates with actual sales over the training period (March quarter 2002 to December quarter 2012). Figure 18, Figure 19 and Figure 20 compare forecasts with actual values over the validation period (March quarter 2013 to December quarter 2015).

Over the training period, the model of category 1 sales appears to fit the data well (Figure 17), with estimates falling within 3.8 per cent of actual sales, on average. The model also appears to capture most of the turning points in the series, correctly predicting the direction of sales more than 88 per cent of the time.

The model of the share of category 2 sales as a proportion of total untreated pine sales was less accurate, with estimates falling within 7.1 per cent of actual sales over the training period. As a result, the derived estimates of category 2 sales were only moderately accurate, falling within 8.5 per cent of actual sales, on average. Furthermore, the direction of category 2 sales was only correctly predicted around 64 per cent of the time.

Figure 17 Category 1 and category 2 untreated pine, historic sales and model estimates, March quarter 2002 to December quarter 2013



Note: Model estimate and actual sales for category 1 sales are identical in December 2002 because an observational dummy was included.
Source: ABARES estimates; FWPA Softwood data series

With regards to out-of-sample forecasting performance, the models performed reasonably well over the validation period but exhibited a tendency to over predict sales (Figure 18, Figure 19 and Figure 20). Taking an average of all forecasts over the validation period, estimates of category 1 sales fell within 3.1 per cent of actual sales while the derived forecasts of category 2 sales fell within 8.1 per cent of actual sales, on average (Table 9). As expected, one-quarter-ahead forecasts were most accurate, with mean forecasts errors of 3.5 per cent and 9.6 per cent for category 1 and category 2 sales, respectively.

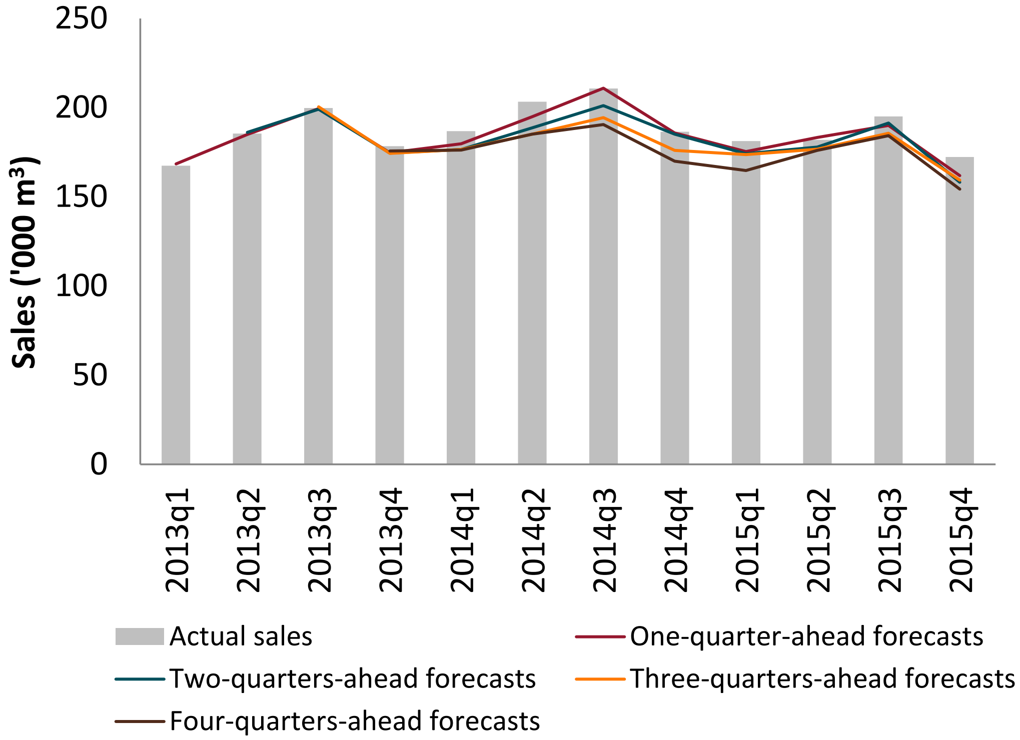
Table 9 Category 1 and category 2 untreated pine, out-of-sample forecasting performance

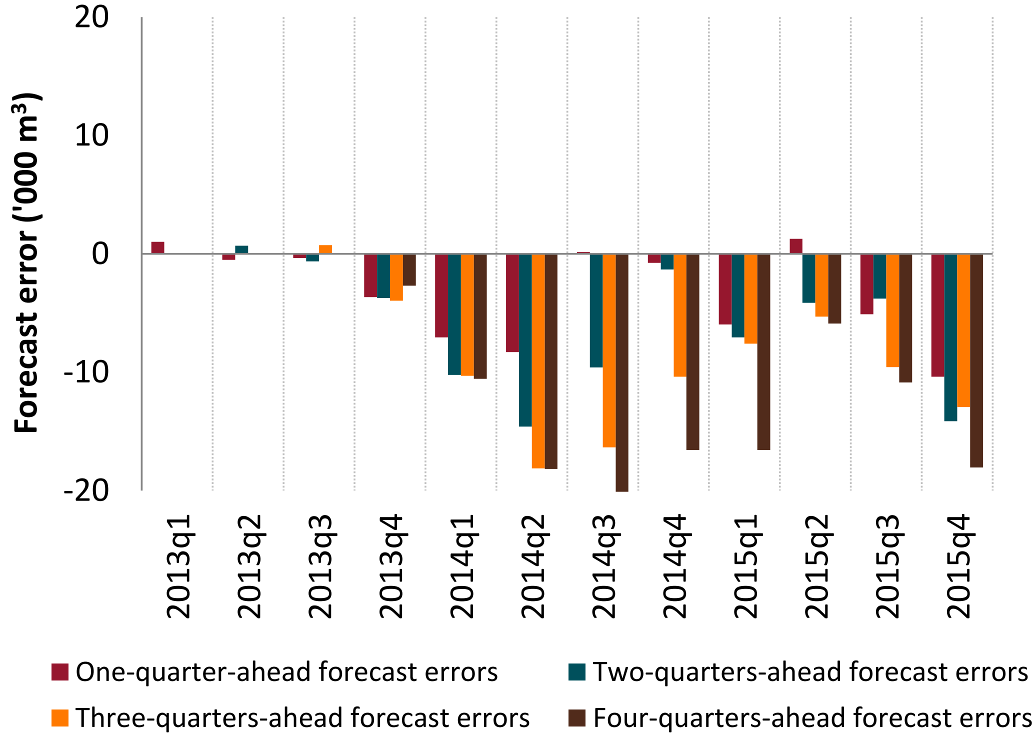
Time horizon	Point forecasting error (MAPE)		Directional forecasting accuracy	
	Cat1 sales (%)	Cat2 sales (%)	Cat1 sales (%)	Cat2 sales (%)
One-quarter-ahead	3.5	9.6	100	92
Two-quarters-ahead	4.5	12.1	100	82
Three-quarters-ahead	4.6	13.3	100	80
Four-quarters-ahead	4.2	14.0	89	56
Average **a**	3.1	8.1	97	77
Total sales over year ahead	2.8	8.1	67	33

a The average forecast error is based on the complete sets of four-quarters-ahead rolling forecasts. It excludes the last three one-quarter-ahead forecasts, last two two-quarters-ahead forecasts and last three-quarters-ahead forecasts. The average forecast error may be less than the horizon-specific forecast errors.
Source: ABARES estimates

The models also predicted the direction of sales over the validation period, with a high degree of accuracy (Table 9). Taking an average of all forecasts over the validation period, the models correctly predicted the direction of category 1 sales 97 per cent of the time and category 2 sales 77 per cent of the time. However, the directional forecasting accuracy for year-ahead sales was poor, particularly for sales of category 2 untreated pine (33 per cent).

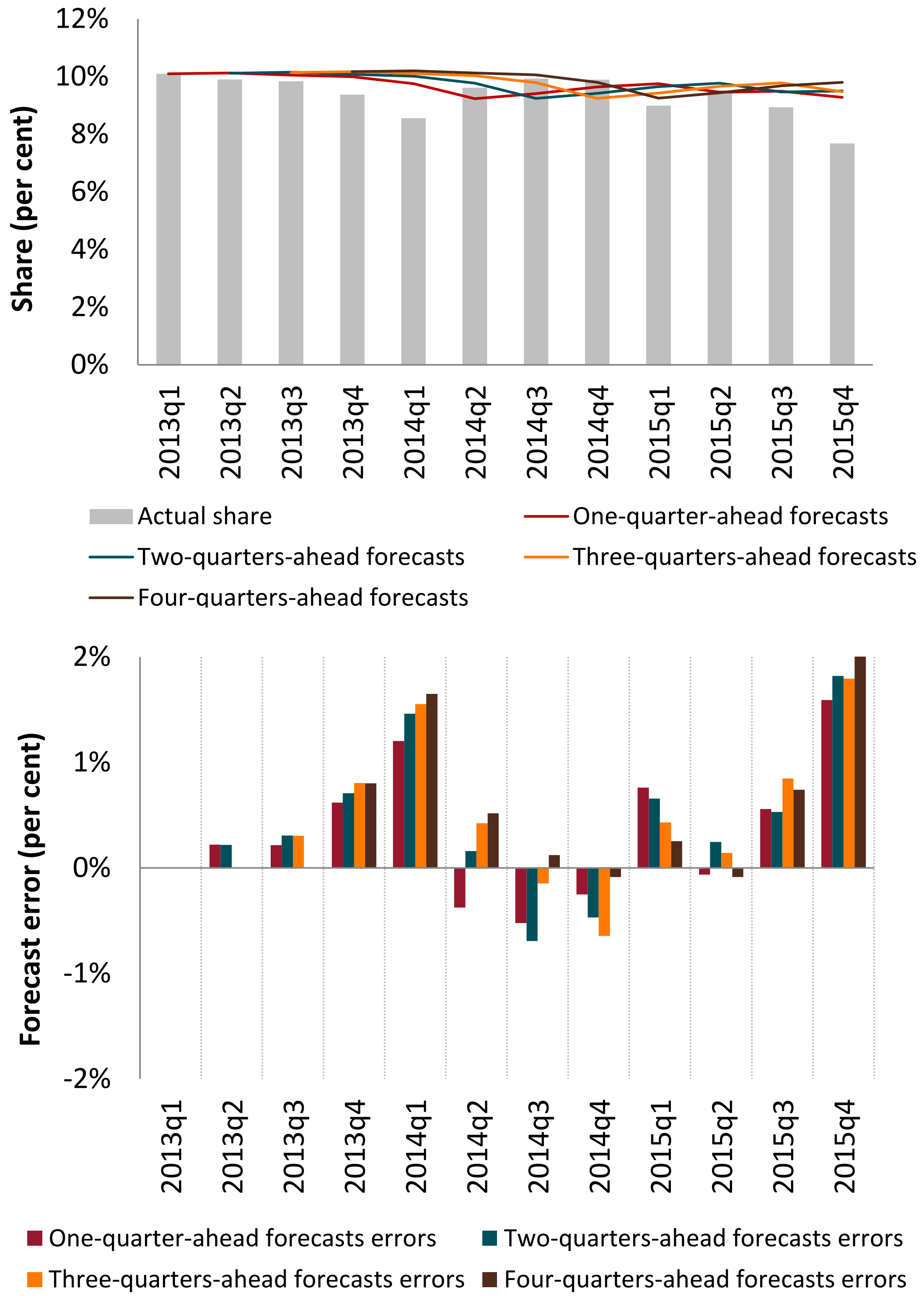
Figure 18 Category 1 Untreated pine, forecasts and actual sales, March quarter 2013 to December quarter 2015





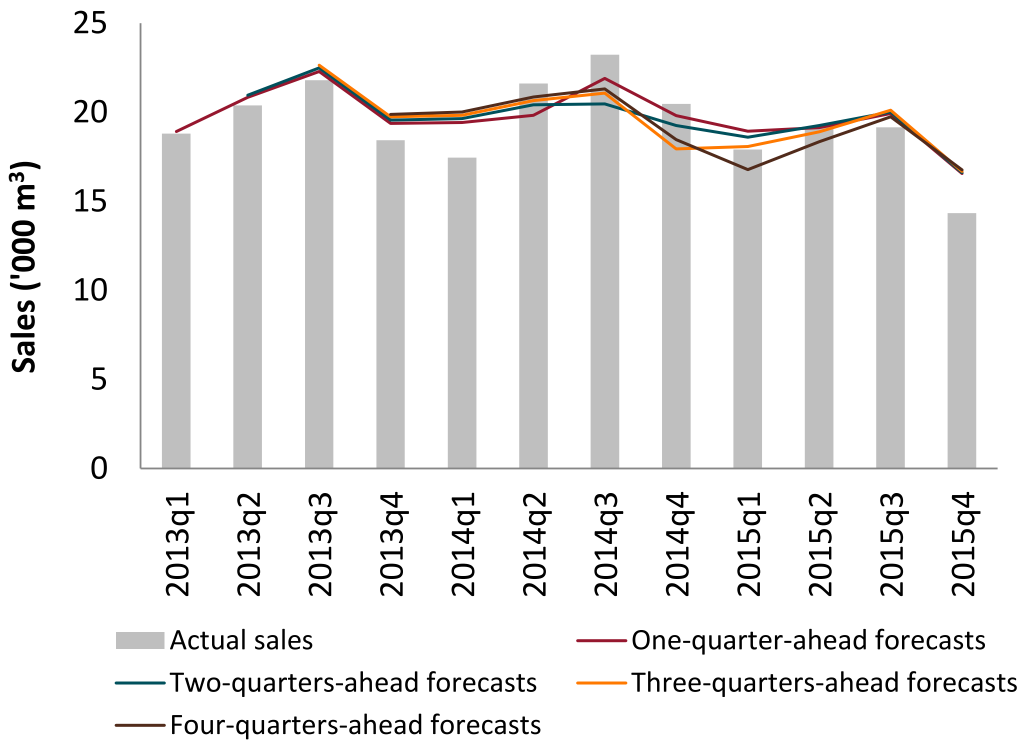
Note: q1, q2, q3 and q4 refer to the March, June, September and December quarters, respectively.
Source: ABARES estimates; FWPA Softwood data series

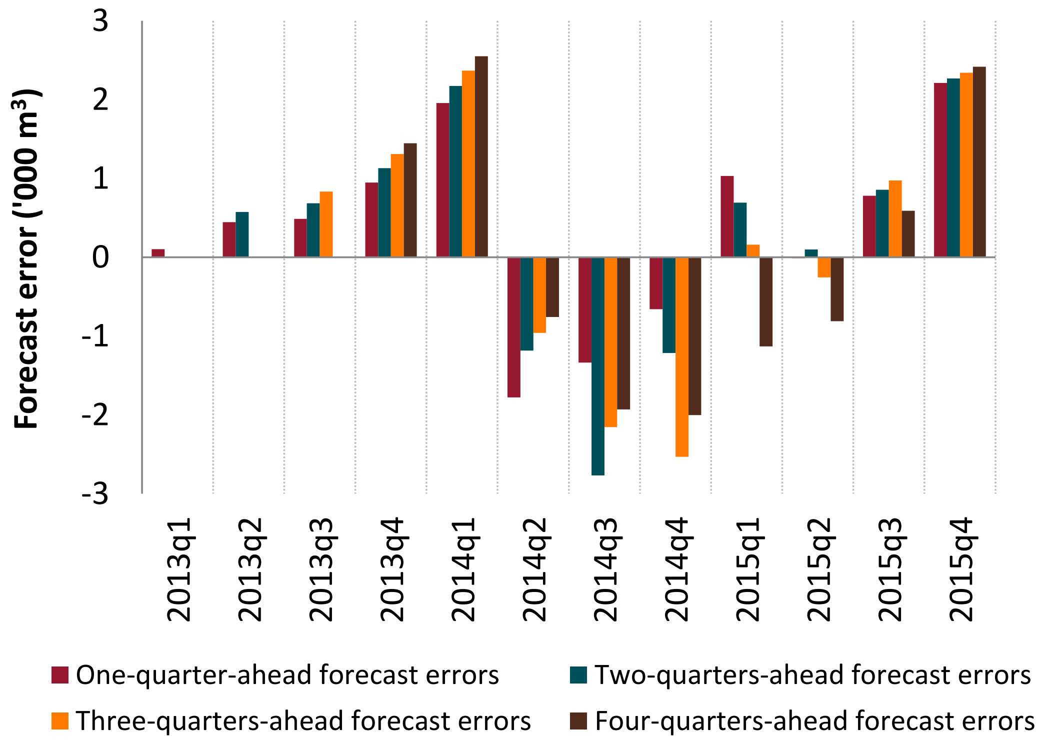
Figure 19 Category 2 share as a proportion of untreated pine, forecasts and actual sales, March quarter 2013 to December quarter 2015



Note: q1, q2, q3 and q4 refer to the March, June, September and December quarters, respectively.
Source: ABARES estimates; FWPA Softwood data series

Figure 20 Category 2 Untreated pine, forecasts and actual sales, March quarter 2013 to December quarter 2015





Note: q1, q2, q3 and q4 refer to the March, June, September and December quarters, respectively.
Source: ABARES estimates; FWPA Softwood data series

5 Model implementation

Timing of forecasts

For forecasts to be a useful tool in decision-making they must be provided sufficiently ahead of time and capture the most recent information. In practice, the delayed release of information used in the models means that producing timely forecasts comes at the expense of using the most up-to-date information. The timing of ABARES forecasts is intended to capture a balance between these two priorities.

Table 10 presents the timeline for updating ABARES models and forecasts. Every quarter, the forecasting equations are re-estimated to include an additional quarter of data for wood product sales and house commencements. Sales data for the wood product series are released on the FWPA dashboard in the month following the end of each quarter. The ABS releases data on house commencements four months after the end of a quarter. Since actual house commencements data are needed to estimate the forecasting models, model coefficients are based on data up to the latest house commencements data. As an example, forecasts for the September quarter onwards are provided in July, as soon as wood product sales for the previous quarter become available (June quarter). However, the models used to generate these forecasts are based on historical data up to and including the September quarter in the previous year.

Forecasts of the three structural pine sales series (category 1 and category 2 untreated pine, and treated pine) are based on forecasts of house commencements over the period for which the sales forecasts are generated. The Housing Industry Association (HIA) provides quarterly forecasts of house commencements for several years into the future. ABARES uses these in the forecasting equations to project wood product sales. However, the HIA forecasts used by ABARES do not contain the most up-to-date housing statistics. This is due to the delay between the release of ABS statistics and provision of the HIA forecasts. For example, ABARES forecasts for the September, December, March and June quarters are based on HIA forecasts released in February. These HIA forecasts are based on actual house commencements data up to the December quarter even though March house commencements data is released.

In addition to re-estimating the existing forecasting models each quarter, the candidate models are reviewed annually to determine whether they remain robust and offer the best out-of-sample forecasts. Given the relatively small sample sizes, particularly for treated pine, model coefficients can change significantly in a relatively short time frame. Consequently, the set of candidate equations and preferred combination of models are likely to change over time.

Forecast uncertainty and error bounds

With the exception of sales of category 2 untreated pine, each set of ABARES forecasts includes 95 per cent confidence intervals or error bounds. These intervals are defined as the range of values in which the actual future value of sales is expected to lie with a probability of 95 per cent. Confidence intervals are not provided for sales of category 2 because the forecast errors are a function of forecast errors for sales of category 1 untreated pine and forecast errors for the share of category 2 sales as a proportion of total untreated pine sales. The statistical distribution of these derived forecast errors are non-normal. Therefore, conventional confidence intervals cannot be calculated.

Table 10 Timeline for updating model parameters and providing forecasts

Month	FWPA softwood data	ABS house commencements data	HIA housing forecasts	ABARES models and forecasts
Jan.	Release December quarter sales.	Release September quarter house commencements for previous year.	–	Provide forecasts for March, June, September and December quarters. Model parameters based on data up to September quarter in previous year. Housing forecasts based on HIA estimates in November of previous year.
Feb.	–	–	Release housing forecasts for December quarter in previous year onwards.	–
Mar.	–	–	–	–
Apr.	Release March quarter sales.	Release December quarter house commencements.	–	Provide forecasts for June, September, December and March quarters. Model parameters based on data up to December quarter in previous year. Housing forecasts based on HIA estimates in February.
May	–	–	Release housing forecasts for March quarter onwards	–
June	–	–	–	–
July	Release June quarter sales.	Release March quarter house commencements.	–	Provide forecasts for September, December, March and June quarters. Model parameters based on data up to March quarter. Housing forecasts based on HIA estimates in May.
Aug.	–	–	Release housing forecasts for June quarter onwards.	–
Sept.	–	–	–	–
Oct.	Release September quarter sales.	Release June quarter house commencements.	–	Provide forecasts for December, March, June and September quarters. Model parameters based on data up to June quarter. Housing forecasts based on HIA estimates in August.
Nov.	–	–	Release housing forecasts for September quarter onwards.	–
Dec.	–	–	–	–

The width of the confidence intervals depend directly on the degree of uncertainty in the estimated models. Models that explain a greater percentage of variation in sales will tend to have smaller confidence intervals. The width of the confidence interval also increases as the time horizon moves further out. Four-quarters-ahead forecasts have a wider confidence interval than one-quarter-ahead forecasts. This is because of the compounding uncertainty around previously forecasted changes in the series.

The estimated error bounds do not take into account uncertainty around HIA forecasts of house commencements or uncertainty around the estimated parameters. That is, the standard errors on which the confidence intervals are based assume that house commencements are forecasted with perfect accuracy and the estimated model parameters are correct. In practice this is not the case and the estimated standard errors will understate the true standard errors.

6 Discussion and limitations

Using the forecasts

The FWPA Softwood data series does not include all producers in the industry and, where possible, excludes sales destined for export. As a result, the series is not representative of national production or sales of any of the wood products. Accordingly, ABARES forecasts should only be interpreted as forecasts of the FWPA Softwood series and not forecasts of national production or sales. The extent to which the ABARES models may be used to forecast sales of individual producers is unknown.

When relying on the estimated models, readers should consider several data-related issues. First, it is assumed that the FWPA Softwood data series accurately reflects the volume of sales for each participating producer. In the interest of confidentiality, participating companies provide individual sales data to an independent third party who then provides aggregated data to the FWPA. Any errors, or inconsistencies that arise in the compilation or aggregation of monthly sales estimates across participating producers could affect the validity of the estimated models and resulting forecasts.

Second, coverage of the data series, in terms of the number of participating companies, changes over the sample period. The inclusion of additional participants in the survey could explain trends observed in the data over the medium term as well as the presence of stochastic trends in the series. Since the forecasting models are based on historical relationships, any trends observed in the data are assumed to be carried forward into the future. However, as the series become more stable over time, the effect of this trend will diminish and the forecasts will become more reliable. In the meantime, inclusion or removal of participants from the series will result in changes that cannot be forecasted by the models presented here.

Third, while the softwood data series is comprehensive, the sample sizes are smaller than ideal when estimating and validating models for forecasting purposes. This is particularly the case for the treated series, which has only 45 observations and 11 years of data at the time of writing this report. Small sample sizes increase uncertainty around coefficient estimates, leading to more variables being classified as statistically insignificant and excluded from models. Furthermore, some of the tests used to validate the in-sample properties of the models necessarily assume that large sample properties of various estimators hold for the finite dataset. This is less likely to be the case for smaller samples, possibly rendering the tests invalid. However, as the sample size grows, these issues will become less pertinent over time.

Further work

In combining multiple models, individual econometric models were selected first without regard to what other models they would be combined with. This means that forecasts may be improved by considering the combination of models when selecting the best econometric models. This report does not consider all the many possible combinations of models because it was assumed that the minor improvements in forecasting performance would not justify the time spent examining every combination.

Forecasting is an evolving process whereby models are continually refined to reflect new information and lessons learnt. In estimating a large number of models for this project, ABARES has developed a library of models to draw from. ABARES will continue to review and refine these models to improve forecasts over time.

Appendix A: Stochastic trends and cointegration

Stochastic trends

Like many economic series, the four wood product sales series considered in this study were found to contain one or more stochastic trends (unit roots). Ordinary least squares estimates obtained from regressions involving non-stationary series have been shown to be invalid.

With quarterly data, unit roots may exist at the quarterly, semi-annual and annual frequencies. The presence of seasonal and non-seasonal unit roots are tested simultaneously using the HEGY procedure (Hylleberg et al. 1990). The procedure involves estimating the regression model shown in Equation A1 and then testing whether the γ coefficients are statistically significant from zero. The significance of γ_1 and γ_2 indicate no unit roots at the quarterly and semi-annual frequencies, respectively, while the joint significance of the coefficients γ_3 and γ_4 indicate no unit root at the annual frequency.

Equation A1

$$\Delta_4 y_t = constant + \alpha_1 * s_1 + \alpha_2 * s_2 + \alpha_3 * s_3 + \beta * trend + \gamma_1 * y_{1,t-1} - \gamma_2 * y_{2,t-1} - \gamma_3 * y_{3,t-1} - \gamma_4 * y_{3,t-2} + lags$$

where:

y_t is the variable of interest and $\Delta_4 y_t = y_t - y_{t-4}$

$y_{1,t-1} = y_{t-1} + y_{t-2} + y_{t-3} + y_{t-4}$

$y_{2,t-1} = y_{t-1} - y_{t-2} + y_{t-3} - y_{t-4}$

$y_{3,t-1} = y_{t-1} - y_{t-3}$

$y_{3,t-2} = y_{t-2} - y_{t-4}$

s_1, s_2 *and* s_3 are orthogonalised seasonal dummies for the March, June and September quarters respectively

trend is a deterministic trend

lags refer to lags of $\Delta_4 y_t$.

The number of lags of $\Delta_4 y_t$ included in the test equations has been shown to affect the validity of the results. Too few lags results in residuals not having white noise properties (rendering inference invalid) and too many lags reduces the power of the test (concluding the presence of unit roots when there are none). To determine the appropriate number of lags, test regressions were run with up to eight lags. The optimal number of lags for each combination of deterministic regressors was selected using the Schwarz Information Criterion (Schwarz 1978). Where residuals did not have the desired properties, additional lags were added until they did.

The test statistics do not have standard distributions and they depend on the deterministic terms included in the equation. Deterministic terms may include a constant, seasonal dummies and a trend. Given the clear seasonality in most of the series, seasonal dummies were included in almost all regressions. Exceptions to this were the exchange rate series and sawmill input price index where only a constant and trend were considered. Where seasonal dummies were included, centred or orthogonalised seasonal dummy variables were used. These shift the mean of the series without contributing to the trend. Critical values for various combinations of deterministic variables are summarised in Table A1.

Table A1 Critical values for HEGY test (48 observations)

Deterministic variables	Non-seasonal unit root				Semi-annual unit root				Annual unit root			
	1%	**2.5%**	**5%**	**10%**	**1%**	**2.5%**	**5%**	**10%**	**1%**	**2.5%**	**5%**	**10%**
C+T+SD	-4.46	-4.04	-3.71	-3.37	-3.80	-3.41	-3.08	-2.73	9.27	7.7	6.55	5.37
C+SD	-3.77	-3.39	-3.08	-2.72	-3.75	-3.37	-3.04	-2.69	9.22	7.68	6.6	5.5
C+T	-4.23	-3.85	-3.56	-3.21	-2.65	-2.24	-1.91	-1.57	4.64	3.7	2.95	2.23
C	-3.66	-3.25	-2.96	-2.62	-2.68	-2.27	-1.95	-1.60	4.78	3.78	3.04	2.32
None	-2.72	-2.29	-1.95	-1.59	-2.67	-2.27	-1.95	-1.60	5.02	4.04	3.26	2.45

C Constant variables. **SD** Centred seasonal dummy variables. **T** Trend variables.
Source: Hylleberg et al. 1990

Given the small sample size, the test regressions were run over the entire sample period (from March 2002 to March 2016). Many of the test regressions had one or more outliers or highly influential observations, as indicated by the Studentised residuals and DFFITS statistics. These observations were removed from the sample and the testing procedure repeated. Both sets of results are presented where this has occurred.

Stochastic trends in wood product sales

Table A2 summarises results from the preliminary HEGY test regressions for the four wood product sales series. The reported figures are the test statistics for the γ coefficients. Test statistics that are insignificant at the 5 per cent level are indicative of a unit root at that frequency.

The test results and inspection of various transformations of the series suggest that all the series tested in Table A2 probably contain at least a non-seasonal unit root (unit root at the quarterly frequency). Total sales of structural pine was the only series that showed evidence of a seasonal unit root at the annual frequency.

Evidence for the existence of seasonal unit roots at the semi-annual frequency was mixed. Landscape wood products exhibited no signs of a semi-annual unit root, but the total structural pine series showed clear evidence of a semi-annual unit root. When the full sample was used, the test regressions for category 1 and category 2 untreated pine, treated pine and total untreated pine sales all indicated the potential presence of a semi-annual unit root. However, when highly influential observations were removed, the statistics became significant, indicating no evidence of a unit root. The results for the share of category 2 sales as a proportion of total untreated pine sales suggest only a non-seasonal unit root, but the results for the share of treated pine as a proportion of total structural pine are mixed.

Based on the body of evidence, it is assumed throughout the model specification process that all series, except total structural pine and the share of treated pine as a proportion of total structural pine, contain only a non-seasonal unit root. In the case of total structural pine, both a non-seasonal and semi-annual unit root are considered. In the case of the share of treated pine as a proportion of total structural pine, both a non-seasonal and annual unit root are considered.

Table A2 HEGY test results, wood product sales

Series	Transformation	Excluded observations	Lags	Deterministic variables	Unit root test statistics			Appropriate difference filter
					Non-seasonal	**Semi-annual**	**Annual**	
Category 1 untreated pine sales	Level	None	2	C, SD, T	-3.14 **b**	-2.61 **b**	12.06	Semi-annual difference
			4	C, SD	-1.12 **b**	-3.29	13.45	Quarterly difference
		2008q3	4	C, SD, T	-0.82 **b**	-4.19	13.92	Quarterly difference
			4	C, SD	-0.67 **b**	-4.37	16.88	Quarterly difference
	Natural logarithm	None	2	C, SD, T	-3.16 **b**	-2.54 **b**	15.47	Semi-annual difference
			4	C, SD	-0.97 **b**	-2.98 **a**	17.44	Semi-annual difference
		2008q3	4	C, SD, T	-0.61 **b**	-3.70	19.21	Quarterly difference
			4	C, SD	-0.58 **b**	-3.84	23.14	Quarterly difference
Category 2 untreated pine sales	Level	None	0	C, SD, T	-2.24 **b**	-4.41	12.02	Quarterly difference
			0	C, SD	-0.54 **b**	-4.81	15.86	Quarterly difference
		2009q1	5	C, SD, T	-3.09 **b**	-3.29	11.55	Quarterly difference
			6	C, SD	-0.21 **b**	-3.58	5.27	Quarterly difference
	Natural logarithm	None	5	C, SD, T	-3.13 **b**	-2.53 **b**	8.73	Semi-annual difference
			2	C, SD	0.01 **b**	-2.98 **a**	12.05	Semi-annual difference
		2009q1, 2012q2	5	C, SD, T	-3.21 **b**	-3.82	11.34	Quarterly difference
			5	C, SD	0.16 **b**	-3.26	13.05	Quarterly difference
Treated pine sales	Level	None	0	C, SD, T	-1.24 **b**	-2.19 **b**	28.52	Semi-annual difference
			0	C, SD	0.61 **b**	-2.15 **b**	28.13	Semi-annual difference
		2008q3, 2010q4, 2015q3, 2016q1	0	C, SD, T	-2.11 **b**	-5.11	28.44	Quarterly -annual difference
			0	C, SD	-1.44 **b**	-4.87	27.66	Quarterly -annual difference

Note: Test regressions were estimated over the period March 2002 to March 2016. All estimates are significant at 5 per cent level unless otherwise specified. **C** Constant or intercept. **SD** Centred seasonal dummy variables. **T** Trend. **a** Insignificant at the 5 per cent level but significant at the 10 per cent level. **b** Insignificant at the 10 per cent level.
Source: ABARES estimates

Table A2 HEGY test results, wood product sales *continued*

Series	Transformation	Excluded observations	Lags	Deterministic variables	Unit root test statistics			Appropriate difference filter
					Non-seasonal	**Semi-annual**	**Annual**	
Treated pine sales	Natural logarithm	None	0	C, SD, T	-2.73 **b**	-3.70	24.18	Quarterly difference
			0	C, SD	-0.7 **b**	-3.40	28.47	Quarterly difference
		2008q3	1	C, SD, T	-2.18 **b**	-3.45	12.25	Quarterly difference
			0	C, SD	-1.14 **b**	-4.48	27.80	Quarterly difference
Landscape wood products sales	Natural logarithm	None	5	C, SD, T	-0.59 **b**	-4.08	9.59	Quarterly difference
			5	C, SD	-2.24 **b**	-4.19	9.90	Quarterly difference
		2005q2, 2005q3, 2009q2	2	C, SD, T	-1.5 **b**	-5.34	29.54	Quarterly difference
			2	C, SD	-3.38	-5.34	32.11	None
Total structural pine sales	Level	None	0	C, SD, T	-1.74 **b**	-2.21 **b**	37.51	Semi-annual difference
			2	C, SD	-1.35 **b**	-2.51 **b**	18.01	Semi-annual difference
		2010q4	0	C, SD, T	-1.84 **b**	-2.22 **b**	44.41	Semi-annual difference
			0	C, SD	-1.49 **b**	-2.23 **b**	43.89	Semi-annual difference
	Natural logarithm	None	0	C, SD, T	-1.54 **b**	-2.06 **b**	35.79	Semi-annual difference
			6	C, SD	-2.19 **b**	-2.43 **b**	5.52 **b**	Annual difference
		2010q4	0	C, SD, T	-1.58 **b**	-2.08 **b**	43.61	Semi-annual difference
			0	C, SD	-1.42 **b**	-2.11 **b**	43.69	Semi-annual difference
Total untreated pine sales	Level	None	2	C, SD,T	-3.17 **b**	-2.48 **b**	12.41	Semi-annual difference
			4	C, SD	-1.07 **b**	-3.34	15.12	Quarterly difference
		2008q3	4	C, SD,T	-0.94 **b**	-4.11	14.73	Quarterly difference
			4	C, SD	-0.65 **b**	-4.31	17.97	Quarterly difference

Note: Test regressions were estimated over the period March 2002 to March 2016. All estimates are significant at the 5 per cent level unless otherwise specified. **C** Constant or intercept. **SD** Centred seasonal dummy variables. **T** Trend. **a** Insignificant at the 5 per cent level but significant at the 10 per cent level. **b** Insignificant at the 10 per cent level.
Source: ABARES estimates

Table A2 HEGY test results, wood product sales *continued*

Series	Transformation	Excluded observations	Lags	Deterministic variables	Unit root test statistics			Appropriate difference filter
					Non-seasonal	**Semi-annual**	**Annual**	
Total untreated pine sales	Natural logarithm	None	4	C, SD, T	-1.52 **b**	-2.97 **a**	18.29	Semi-annual difference
			4	C, SD	-0.91 **b**	-3.07	22.61	Quarterly difference
		2008q3, 2010q4	4	C, SD, T	-0.67 **b**	-3.91	23.75	Quarterly difference
			4	C, SD	-0.53 **b**	-4.08	28.95	Quarterly difference
Share of category 2 sales as a proportion of total untreated pine	Level	None	0	C, SD, T	-1.07 **b**	-3.62	10.62	Quarterly difference
			0	C, SD	-1.34 **b**	-3.79	11.70	Quarterly difference
			0	C, SD	-1.29 **b**	-3.67	12.28	Quarterly difference
Share of treated pine sales as a proportion of total structural pine	Level	2015q4	3	C, SD	-2.10 **b**	-2.76 **a**	3.52 **b**	Annual difference
			1	C, SD	0.34 **b**	-3.84	9.86	Quarterly difference
			0	C, SD	0.30 **b**	-4.22	13.89	Quarterly difference

Note: Test regressions were estimated over the period March 2002 to March 2016. All estimates are significant at the 5 per cent level unless otherwise specified. **C** Constant or intercept. **SD** Centred seasonal dummy variables. **T** Trend. **a** Insignificant at the 5 per cent level but significant at the 10 per cent level. **b** Insignificant at the 10 per cent level.
Source: ABARES estimates

Stochastic trends in other series

The HEGY test statistics for other series are summarised in Table A3. Almost all the series tested showed evidence of non-seasonal unit roots. The exception was the sawmill input price index. This showed evidence of a non-seasonal unit root, but the results were dependent on the combination of deterministic variables included in the test regressions.

House commencements and the value of residential alterations and additions also showed evidence of containing non-seasonal unit roots. When the full sample was used, house commencements appeared to include a semi-annual unit root. However, the statistics were significant at the 10 per cent level and removal of a number of highly influential observations reversed the result. The value of residential alterations and additions exhibited clear signs of a unit root at the semi-annual and annual frequencies, depending on which deterministic variables were included in the test regressions. Both possibilities were considered throughout the model development.

Cointegration

Two or more variables are said to be cointegrated if they have the same order of integration and share one or more common stochastic trends. Cointegrated variables can be represented using an error correction model where deviations from a stationary long-run equilibrium relationship can help to explain short-term movements in the series.

Johansen test

With the order of integration for each of the series determined using the HEGY test, the presence of one or more cointegrating relationships between various series of the same order of integration was tested using the Johansen procedure (1988). This involves first estimating an undifferenced vector autoregressive (VAR) model to determine the appropriate number of lags and then testing the rank of matrix Π to determine the number of cointegrating relationships in equation A2.

Equation A2:

$$\Delta y_t = constant + \alpha_1 {*} s_1 + \alpha_2 {*} s_2 + \alpha_3 {*} s_3 + \beta {*} trend + \pi {*} (y_t + constant + \delta {*} trend) + lags$$

where:

y_t is a vector of the variables of interest and $\Delta y_t = y_t - y_{t-1}$

s_1, s_2 *and* s_3 are orthogonalised seasonal dummies for the March, June and September quarters respectively

trend is a deterministic trend

lags refer to lags of Δy_t.

Seasonal cointegration between series with seasonal unit roots is a possibility. However, the results of the HEGY tests showed only weak evidence of seasonal unit roots (Table A2 and Table A3). As such, only non-seasonal cointegration is considered.

Table A3 HEGY test results, other series

Series	Transformation	Excluded observations	Lags	Deterministic variables	Unit root test statistics			Appropriate difference filter
					Non-seasonal	Semi-annual	Annual	
House commencements	Level	None	3	C, SD, T	-2.81 **b**	-2.97 **a**	18.14	Semi-annual difference
			3	C, SD	-2.83 **b**	-3.07	17.53	Quarterly difference
		2008q3, 2009q4	3	C, SD, T	-2.94 **b**	-4.38	19.42	Quarterly difference
			3	C, SD	-2.88 **b**	-4.48	18.50	Quarterly difference
	Natural logarithm	None	0	C, SD, T	-2.55 **b**	-2.98 **a**	35.03	Semi-annual difference
			0	C, SD	-2.42 **b**	-2.91 **a**	34.82	Semi-annual difference
		2008q3, 2009q4	4	C, SD, T	-2.91 **b**	-3.34	13.75	Quarterly difference
			4	C, SD	-2.79 **b**	-3.17	12.87	Quarterly difference
Other residential commencements	Level	None	0	C, SD, T	-1.12 **b**	-3.54	19.18	Quarterly difference
			0	C, SD	0.40 **b**	-3.49	18.65	Quarterly difference
	Natural logarithm	None	0	C, SD, T	1.95 **b**	-3.12	25.28	Quarterly difference
			0	C, SD	-0.53 **b**	-3.05	24.75	Quarterly difference
Value of alterations and additions	Level	None	2	C, SD, T	-3.11 **b**	-2.56 **b**	8.37	Semi-annual difference
			3	C, SD	-1.69 **b**	-2.51 **b**	5.08 **b**	Annual difference
		2009q2	2	C, SD, T	-3.05 **b**	-3.01 **a**	8.70	Semi-annual difference
			3	C, SD	-1.65 **b**	-2.93 **a**	5.15 **b**	Annual difference
	Natural logarithm	2009q2	8[a]	C, SD, T	-1.51 **b**	-2.37 **b**	4.45 **b**	Annual difference
			8[b]	C, SD	-2.14 **b**	-2.36 **b**	4.49 **b**	Annual difference
Value of work done on houses	Level	None	0	C, SD, T	-2.11 **b**	-3.90	19.21	Quarterly difference
			0	C, SD	-0.71 **b**	-3.73	17.98	Quarterly difference
	Natural logarithm	None	0	C, SD, T	-2.00 **b**	-4.08	16.15	Quarterly difference
			0	C, SD	-1.03 **b**	-4.03	15.68	Quarterly difference

Note: Test regressions were estimated over the period March 2002 to December 2015. All estimates are significant at the 5 per cent level unless otherwise specified. **C** Constant or intercept. **SD** Centred seasonal dummy variables. **T** Trend. **a** Insignificant at the 5 per cent level but significant at the 10 per cent level. **b** Insignificant at the 10 per cent level.
Source: ABARES estimates

Table A3 HEGY test results, other series *continued*

Series	Transformation	Excluded observations	Lags	Deterministic variables	Unit root test statistics			Appropriate difference filter
					Non-seasonal	Semi-annual	Annual	
Value of non-residential work done	Level	None	2	C,SD,T	-0.85 **b**	-4.13	14.83	Quarterly difference
			2	C,SD	-2.51 **b**	-4.22	15.08	Quarterly difference
	Natural logarithm	2010q1	8	C,SD,T	-2.45 **b**	-3.18	7.64	Quarterly difference
			2	C,SD	-3.89	-4.38	24.89	None
NZD/AUD exchange rate	Level	None	0	C	-1.47 **b**	-5.33	19.38	Quarterly difference
			0	None	-0.24 **b**	-5.23	18.34	Quarterly difference
	Natural logarithm	None	0	C	-1.48 **b**	-5.28	19.01	Quarterly difference
			0	None	-0.69 **b**	-5.20	18.10	Quarterly difference
EUR/AUD exchange rate	Level	2008q4, 2013q3	0	C	-0.97 **b**	-4.47	51.76	Quarterly difference
			0	None	1.93 **b**	-4.50	51.44	Quarterly difference
	Natural logarithm	2008q4, 2013q3	0	C	-1.16 **b**	-4.86	45.90	Quarterly difference
			0	None	-2.34 **b**	-4.90	46.59	Quarterly difference
USD/AUD exchange rate	Level	2008q4, 2013q3	0	C	-2.51 **b**	-4.90	29.86	Quarterly difference
			0	None	-0.90 **b**	-4.86	15.19	Quarterly difference
	Natural logarithm	2008q4, 2013q3	0	C	-2.99 **b**	-5.55	29.05	Quarterly difference
			0	None	-3.15 **b**	-5.57	29.32	Quarterly difference
Sawmill input price index	Natural logarithm	2008q4	5	C,T	-3.63 **b**	-5.38	29.36	None
			5	C	-1.21 **b**	-5.06	25.21	Quarterly difference
			5	None	-3.44	-5.05	26.90	None
Road transport cost index	Natural logarithm	2008q3, 2009q1	0	C,T	-0.60 **b**	-5.08	26.59	Quarterly difference
			0	C	-1.90 **b**	-5.13	27.06	Quarterly difference
			0	None	2.52 **b**	-5.16	28.76	None

Note: Test regressions were estimated over the period March 2002 to December 2015. All estimates are significant at the 5 per cent level unless otherwise specified. **C** Constant or intercept. **SD** Centred seasonal dummy variables. **T** Trend. **a** Insignificant at the 5 per cent level but significant at the 10 per cent level. **b** Insignificant at the 10 per cent level.
Source: ABARES estimates

Similar to the HEGY test, the results of the Johansen procedure are highly sensitive to the number of lags included in the model and the distributions of the test statistics are dependent on the combination of deterministic regressors included in the model. The number of lags in the undifferenced VAR models was determined using the Schwarz information criterion and three sets of assumptions about deterministic variables are considered:

1) an intercept in the cointegrating equation
2) an intercept in both the cointegrating equation and VAR
3) an intercept and trend in the cointegrating equation and an intercept in the VAR.

However, in all test regressions centred seasonal dummies were required to make the residuals have the necessary white noise properties.

In all of the test regressions, one or more highly influential observations had to be removed in order to correct non-normality in the residuals.

Johansen test results

Table A4 presents the results of formal tests of cointegration of category 1 and category 2 sales, and between untreated and treated pine. Dummy variables for a number of statistically significant observations needed to be included to give the residuals the necessary properties. Based on the Schwarz criterion, only one lag was included in the undifferenced VARs and therefore no lags were included in the estimated VECs. Significance of the test statistics at the 5 per cent level indicates the presence of a cointegrating relationship.

All test results showed evidence of a single cointegrating relationship between category 1 and category 2 sales. Consequently, a vector error correction model is considered a viable approach to jointly forecasting the category 1 and category 2 sales series.

In contrast, results were mixed for a cointegrating relationship between total untreated pine and treated pine sales. In the simplest model, which included a constant in the cointegrating equation and seasonal dummies in the VAR, the tests suggested that the two series were cointegrated. In all other cases, there was no evidence of cointegration between the two series.

Table A4 Johansen test results, untreated pine

Series	Transformation	Excluded observations	Deterministic variables: Cointegrating equation	Deterministic variables: VAR equation	Lags	Hypothesised number of cointegrating equations	Trace test: Test statistic	Trace test: Critical value	Max-Eigenvalue statistic: Test statistic	Max-Eigenvalue statistic: Critical value
Category 1 untreated pine, Category 2 untreated pine	Level	2004q1, 2008q3, 2010q4	C	SD	0	None	22.39	20.26	21.14	15.89
						At most one	1.26 **a**	9.16	1.26 **a**	9.16
			C	C, SD	0	None	21.98	15.49	21.12	14.26
						At most one	0.85 **a**	3.84	0.85 **a**	3.84
			C, T	C, SD	0	None	29.71	25.87	21.29	19.39
						At most one	8.42 **a**	12.52	8.42 **a**	12.52
	Natural logarithm	2004q1, 2008q3, 2010q4	C	SD	0	None	21.14 **a**	20.26	20.08	15.89
						At most one	1.06 **a**	9.16	1.34 **a**	9.16
			C	C, SD	0	None	20.70	15.49	20.04	14.26
						At most one	0.67 **a**	3.84	0.67 **a**	3.84
			C T	C, SD	1	None	28.74	25.87	20.32	19.39
						At most one	8.42 **a**	12.52	8.42 **a**	12.52
Total untreated pine, Treated pine	Level	2008q3	C	SD	0	None	23.71	20.26	20.26	15.89
						At most one	0.68 **a**	9.16	0.68 **a**	9.16
			C	C , SD	0	None	1.79 **a**	15.49	1.63 **a**	14.26
						At most one	0.16 **a**	3.84	0.16 **a**	3.84
			C , T	C , SD	0	None	11.35 **a**	25.87	11.18 **a**	19.39
						At most one	0.17 **a**	12.52	0.17 **a**	12.52

Note: Test regressions were estimated over the period March 2002 to March 2016. All estimates are significant at the 5 per cent level unless otherwise specified. **C** Constant or intercept. **SD** Centred seasonal dummy variables. **T** Trend. **a** Insignificant at the 5 per cent level.

Table A4 Johansen test results, untreated pine *continued*

Series	**Transformation**	**Excluded observations**	**Deterministic variables**		**Lags**	**Hypothesised number of cointegrating equations**	**Trace test**		**Max-Eigenvalue statistic**	
			Cointegrating equation	**VAR equation**			**Test statistic**	**Critical value**	**Test statistic**	**Critical value**
Total untreated pine, Treated pine	Natural logarithm	2008q3, 2010q4	C	SD	1	None	40.67	20.26	38.03	15.89
						At most one	2.62 **a**	9.16	2.62 **a**	9.16
			C	C, SD	1	None	21.92	15.49	21.41	14.26
						At most one	0.50 **a**	3.84	0.50 **a**	3.84
			C, T	C, SD	1	None	38.29	25.87	37.44	19.39
						At most one	0.85 **a**	12.52	0.85 **a**	12.52

Note: Test regressions were estimated over the period March 2002 to March 2016. All estimates are significant at the 5 per cent level unless otherwise specified. **C** Constant or intercept. **SD** Centred seasonal dummy variables. **T** Trend. **a** Insignificant at the 5 per cent level.

Appendix B: Model estimates and validation

This appendix presents detailed results and estimates of out-of-sample forecasting performance for all candidate models that were found to have suitable in-sample properties. The first part covers all models of individual product sale series (LNDSCP, TREAT and CAT1) and total sales series (STRUCT and UNTREAT); the second part covers models describing the ratio of two series (RATIO_STRUCT and RATIO_UNTREAT); and the third part covers the vector error correction models (VEC_STRUCT and VEC_UNTREAT). The preferred models are selected on the basis of their RMSE, but the mean absolute percentage errors (MAPE) are also presented for convenience. Table B1 summarises the variables used in the candidate models presented in this appendix.

Table B1 Variable summary

Variable name	Description	Source
lndscp	Quarterly sales of landscape wood products	FWPA Softwood data series
treat	Quarterly sales of treated pine	FWPA Softwood data series
cat1	Quarterly sales of category 1 untreated pine	FWPA Softwood data series
cat2	Quarterly sales of category 2 untreated pine	FWPA Softwood data series
untreat	Quarterly sales of total untreated pine (comprised of category 1 and category 2 untreated pine)	FWPA Softwood data series
struct	Quarterly sales of total structural pine (comprised of treated pine and total untreated pine)	FWPA Softwood data series
cat2_share	Share of category 2 untreated pine sales as a proportion of total untreated pine sales	FWPA Softwood data series
treat_share	Share of treated pine sales as a proportion of total structural pine sales	FWPA Softwood data series
hc	Quarterly house commencements	ABS 2016b
oc	Quarterly other residential commencements	ABS 2016b
smc	Quarterly price index for sawmill material inputs	ABS 2016d
trans	Quarterly price index for road transport services	ABS 2016d
er_nz	Quarterly NZ/Australian dollar exchange rate	ABS 2016a
AR(p)	Autoregressive process of order ‘p’	Time series process
MA(q)	Moving average process of order 'q’	Time series process
d_1, d_2 and d_3	Dummy variables for March, June and December quarters, respectively	Deterministic term
outlier	Dummy variable for specified observation	Deterministic term
trend	Indicates a time trend is included in the model	Deterministic term
constant	Indicates an intercept is included in the model	Deterministic term

Models of individual sales series

LNDSCP

Candidate models

Table B2 presents estimation results for four candidate models of landscape wood products sales, identified as having suitable in-sample properties. All candidate models assume that the landscape wood products sales series contains a single unit root, and estimate the change in natural logarithm of sales. Key variables include the change in natural logarithm of house commencements and past sales. LNDSCP_3 includes a first order moving average process. A number of observational dummies were included across the four candidate models to account for statistically significant individual observations.

Table B2 LNDSCP, model estimates

Model	LNDSCP_1	LNDSCP_2	LNDSCP_3	LNDSCP_4
Estimation				
– dependent variable	$\Delta\ln(lndscp_t)$	$\Delta\ln(lndscp_t)$	$\Delta\ln(lndscp_t)$	$\Delta\ln(lndscp_t)$
– observations	41	42	42	42
– method	LS	LS	ARMA	LS
Variable coefficients				
– constant	0.117	0.141	0.173	0.101
– d_1	-0.136 **a**	-0.218	-0.297	-0.122
– d_2	-0.132	-0.135	-0.199	-0.050 **b**
– d_3	0.142	0.088 **b**	0.078 **b**	0.075
– d_1*trend	-0.006	–	–	-0.006
– $\Delta\ln(lndscp_{t-1})$	-0.279	-0.409	-0.590	-0.113 **a**
– $\Delta\ln(lndscp_{t-2})$	–	-0.200 **b**	–	–
– $\Delta\ln(lndscp_{t-3})$	–	-0.188	–	–
– MA(1)	–	–	-0.268	–
– outlier_2002q3	–	–	–	0.221
– outlier_2002q4	–	–	–	-0.152
– outlier _2003q2	–	–	–	-0.298
– outlier _2003q3	–	–	–	0.259
– outlier _2005q2	0.513	0.532	0.535	0.462
– outlier _2005q3	-0.510	-0.399	–	-0.513
– outlier _2008q3	–	–	–	-0.219
– outlier _2009q2	0.365	-0.397	–	-0.331
Model fit				
– Adjusted R-squared	0.81	0.81	0.59	0.94
– AIC	-1.79	-1.78	-1.04	-2.79
– SC	-1.42	-1.36	-0.71	-2.21

Note: Results are for models estimated over the training period (March 2002 to December 2012). Coefficient estimates of the preferred model differ from those of the most up-to-date version presented in Section 4. All estimates are significant at the 5 per cent level unless otherwise specified. **a** Insignificant at the 5 per cent level but significant at the 10 per cent level. **b** Insignificant at the 10 per cent level.
Source: ABARES estimates

Out-of-sample forecasting performance

Table B3 summarises the out-of-sample forecasting performance of the four single equation models for landscape wood products sales. While LNDSCP_3 and LNDSCP_4 generated the most accurate four- and one-quarter-ahead forecasts, respectively, LNDSCP_2 generated the most accurate forecasts over all other time horizons and had the lowest average forecast error over the validation period. LNDSCP_2 also correctly predicted the direction of sales more than 90 per cent of the time. For these reasons LNDSCP_2 is the preferred model for landscape wood products sales.

Table B3 LNDSCP, out-of-sample forecasting performance

Error measure	Forecast time horizon	LNDSCP_1	LNDSCP_2 a	LNDSCP_3	LNDSCP_4
RMSE	One-quarter-ahead	3 972	3 636	3 806	3 277
	Two-quarters-ahead	5 274	4 095	4 792	4 920
	Three-quarters-ahead	5 833	5 211	5 999	5 933
	Four-quarters-ahead	5 848	5 102	4 882	6 841
	Average **b**	8 061	6 675	7 813	8 212
	Total sales over year ahead	17 976	14 665	17 467	19 112
MAPE (%)	One-quarter-ahead	12.9	13.1	13.7	11.3
	Two-quarters-ahead	16.2	13.9	15.3	14.6
	Three-quarters-ahead	15.7	16.2	18.7	14.6
	Four-quarters-ahead	14.4	13.2	12.5	15.1
	Average **b**	11.7	10.9	12.6	11.5
	Total sales over year ahead	11.5	10.7	12.9	11.8
Directional accuracy (%)	One-quarter-ahead	83	83	83	92
	Two-quarters-ahead	100	100	91	100
	Three-quarters-ahead	80	80	80	90
	Four-quarters-ahead	100	100	100	100
	Average **c**	91	91	89	95
	Total sales over year ahead	89	100	89	67

Note: Results are for models estimated over the training period (March 2002 to December 2012). A lower RMSE or MAPE indicates more accurate point forecasts over the validation period. **a** Preferred model. **b** Average forecast errors across all rolling forecasts estimated over the validation period. **c** Average directional accuracy across all rolling forecasts estimated over the validation period.
Source: ABARES estimates

TREAT

Candidate models

Table B4 presents estimation results for three candidate single equation models of treated pine sales identified as having suitable in-sample properties. All candidate models assume that the treated pine sales series contains a single unit root and estimate either the change in sales or the change in the natural logarithm of sales. Key variables include changes in house commencements and past sales. Observational dummies for September and December quarters of 2005 were found to be statistically significant in models 2, 3 and 4.

Table B4 TREAT, model estimates

Model	TREAT_1	TREAT_2	TREAT_3
Estimation			
– dependent variable	$\Delta treat_t$	$\Delta ln(treat_t)$	$\Delta ln(treat_t)$
– observations	31	30	30
– method	LS	LS	ARMA
Variable coefficients			
– constant	-5 424	-0.109	-0.130
– d_1	15 075	0.279	0.276
– d_2	5 764 **a**	0.129	0.168
– d_3	10 428	0.119	0.141
– $\Delta ln(treat_{t-1})$	–	0.353	0.458
– Δhc_t	2.678	–	–
– $\Delta ln(hc_t)$	–	0.922	0.719
– AR(4)	–	–	-0.445
– MA(1)	–	–	-0.322 **b**
– MA(4)	–	–	0.580
– outlier_2005q3	–	0.355	0.375
– outlier_2005q4	–	–	–
Model fit			
– Adjusted R-squared	0.68	0.84	0.90
– AIC	20.05	-2.53	-3.05
– SC	20.28	-2.20	-2.89

Note: Results are for models estimated over the training period (March 2002 to December 2012). Coefficient estimates of the preferred model differ from those of the most up-to-date version presented in Section 4. All estimates are significant at the 5 per cent level unless otherwise specified. **a** Insignificant at the 5 per cent level but significant at the 10 per cent level. **b** Insignificant at the 10 per cent level.
Source: ABARES estimates

Out-of-sample forecasting performance

Table B5 summarises the out-of-sample forecasting performance of the three candidate models for treated pine sales identified as having suitable in-sample properties. TREAT_1 generated the most accurate forecasts of treated pine over all time horizons, as well as the most accurate predictions of the direction of sales up to and including three-quarters-ahead. For these reasons, TREAT_1 is the preferred model for treated pine sales.

Table B5 TREAT, out-of-sample forecasting performance

Error measure	Forecast time horizon	TREAT_1 a	TREAT_2	TREAT_3
RMSE	One-quarter-ahead	5 716	8 611	8 989
	Two-quarters-ahead	7 835	13 798	10 394
	Three-quarters-ahead	7 494	15 054	9 901
	Four-quarters-ahead	8 411	17 056	10 742
	Average **b**	8 310	20 021	10 569
	Total sales over year ahead	15 893	45 622	20 216
MAPE (%)	One-quarter-ahead	4.5	8.3	6.0
	Two-quarters-ahead	5.0	10.5	6.3
	Three-quarters-ahead	5.4	9.4	7.0
	Four-quarters-ahead	5.8	11.4	7.2
	Average **b**	3.2	7.3	4.1
	Total sales over year ahead	3.2	6.3	3.9
Directional accuracy (%)	One-quarter-ahead	83	75	83
	Two-quarters-ahead	82	73	82
	Three-quarters-ahead	60	60	60
	Four-quarters-ahead	67	89	78
	Average **c**	73	74	76
	Total sales over year ahead	100	89	89

Note: Results are for models estimated over the training period (March 2002 to December 2012). A lower RMSE or MAPE indicates more accurate point forecasts over the validation period. **a** Preferred model. **b** Average forecast errors across all rolling forecasts estimated over the validation period. **c** Average directional accuracy across all rolling forecasts estimated over the validation period.
Source: ABARES estimates

CAT1

Candidate models

Table B6 presents estimation results for eight candidate models of category 1 untreated pine sales identified as having suitable in-sample properties. All candidate models assume that sales of category 1 untreated pine contains a single non-seasonal unit root by estimating the quarterly change in the natural logarithm of sales. Key explanatory variables include changes in house commencements, sawmill input costs, road transport costs, the NZ/Australian dollar exchange rate and past growth in sales. Models 3 and 4 include a first order moving average process. An observational dummy for December 2002 was found to be statistically significant in all models except models 3 and 8.

Out-of-sample forecasting performance

Table B7 summarises the out-of-sample forecasting performance of the five single equation models for category 1 untreated pine sales. CAT1_2 generated the most accurate two-quarters-ahead forecasts, but CAT1_1 generated the most accurate forecasts over all other time horizons. CAT1_1 also generated more accurate predictions of the direction of sales over almost all time horizons, making it the preferred model for category 1 sales.

Table B6 CATEGORY 1, model estimates

Model	**CAT1_1**	**CAT1_2**	**CAT1_3**	**CAT1_4**	**CAT1_5**	**CAT1_6**	**CAT1_7**	**CAT1_8**
Estimation								
– dependent variable	$\Delta\ln(cat1_t)$	$\Delta\ln(cat1_t)$	$\Delta\ln(cat1_t)$	$\Delta\ln(cat1_t)$	$\Delta\ln(cat1_t)$	$\Delta\ln(cat1_t)$	$\Delta\ln(cat1_t)$	$\Delta\ln(cat1_t)$
– observations	43	43	43	43	39	39	43	42
– method	LS	LS	LS	LS	LS	ARMA ML	LS	ARMA ML
Variable coefficients								
– constant	-0.104	0.256 **b**	-0.095	-0.104	-0.091	-0.100	0.384	0.296
– d_1	0.157	0.163	0.149	0.174	0.156	0.162	0.152	0.179
– d_2	0.114	0.112	0.120	0.111	0.115	0.112	0.120	0.112
– d_3	0.126	0.125	0.135	0.113	0.123	0.113	0.138	0.112
– $\Delta^4\log(cat1_{t-1})$	–	–	–	–	0.101 **b**	0.137	–	–
– $\Delta\log(hc_t)$	0.664	0.693	0.615	1.132	0.652	0.664	0.632	1.213
– $\Delta\log(hc_t)$*trend	–	–	–	-0.015	–	–	–	-0.018
– $\log(smc_{t-1})$	–	-0.082	–	–	–	–	-0.108	-0.091
– $\Delta\log(trans_t)$	–	–	-1.190 **b**	–	-1.179 **b**	–	-1.666	–
– $\Delta\log(er\_nz_t)$	–	–	–	-0.641	–	–	–	-0.828
– MA(1)	–	–	–	–	–	-0.375 **b**	–	-0.458
– outlier_2002q4	0.232	0.228	0.231	0.260	–	–	0.224	0.253
Model fit								
– Adj. R-squared	0.73	0.75	0.74	0.79	0.76	0.76	0.79	0.84
– AIC	-2.96	-3.03	-3.00	-3.17	-3.06	-3.05	-3.16	-3.40
– SC	-2.71	-2.74	-2.71	-2.84	-2.76	-2.71	-2.84	-2.95

Note: Results are for models estimated over the training period (March 2002 to December 2012). Coefficient estimates of the preferred model differ from those of the most up-to-date version presented in Section 4. All estimates are significant at the 5 per cent level unless otherwise specified. **a** Insignificant at the 5 per cent level but significant at the 10 per cent level. **b** Insignificant at the 10 per cent level.
Source: ABARES estimates

Table B7 CATEGORY 1, out-of-sample forecasting performance

Error measure	Forecast time horizon	CAT1_1 a	CAT1_2	CAT1_3	CAT1_4	CAT1_5	CAT1_6	CAT1_7	CAT1_8
RMSE	One-quarter-ahead	5 174	5 360	6 703	6 635	6 503	5 773	6 690	8 077
	Two-quarters-ahead	7 414	7 274	10 323	7 954	10 692	8 747	8 934	10 460
	Three-quarters-ahead	7 658	8 065	12 570	9 593	14 253	11 376	10 205	12 013
	Four-quarters-ahead	8 588	10 644	14 307	10 631	18 397	15 112	11 633	13 644
	Average **b**	10 592	11 751	16 605	13 883	19 906	16 427	14 339	15 971
	Total sales over year ahead	23 611	26 803	38 249	34 454	46 844	39 000	32 491	36 596
MAPE (%)	One-quarter-ahead	3.5	3.3	4.5	3.9	4.4	3.8	4.6	4.8
	Two-quarters-ahead	4.5	4.4	6.5	4.9	6.7	5.4	5.0	5.6
	Three-quarters-ahead	4.6	4.4	7.4	4.7	8.1	6.3	4.8	6.5
	Four-quarters-ahead	4.2	5.4	6.9	5.2	9.0	7.2	5.9	7.5
	Average **b**	3.1	3.3	4.8	3.9	5.5	4.5	3.8	4.3
	Total sales over year ahead	2.8	3.4	4.8	4.0	5.5	4.6	3.7	4.8
Directional accuracy (%)	One-quarter-ahead	100	100	100	83	100	100	100	83
	Two-quarters-ahead	100	100	91	91	91	100	91	91
	Three-quarters-ahead	100	90	90	90	90	100	80	90
	Four-quarters-ahead	8	89	78	78	78	78	78	100
	Average **c**	97	95	90	86	90	94	87	91
	Total sales over year ahead	67	67	44	56	56	56	44	56

Note: Results are for models estimated over the training period (March 2002 to December 2012). A lower RMSE or MAPE indicates more accurate point forecasts over the validation period. **a** Preferred model. **b** Average forecast errors across all rolling forecasts estimated over the validation period. **c** Average directional accuracy across all rolling forecasts estimated over the validation period.
Source: ABARES estimates

STRUCT

Candidate models

Table B8 presents estimation results for three candidate models of total structural pine sales found to have suitable in-sample properties. All candidate models assume that the total structural pine sales series contains a non-seasonal unit root and an additional seasonal unit root at the semi-annual frequency, by estimating the semi-annual change in the natural logarithm of sales. Key explanatory variables include changes in house commencements, road transport costs and past values of sales.

Out-of-sample forecasting performance

Table B9 presents a summary of the out-of-sample forecasting performance of the three single equation models of total structural pine sales identified as having suitable in-sample properties. STRUCT_1 generated the most accurate forecasts of treated pine over all time horizons and is therefore the preferred model for total structural pine sales.

Table B8 STRUCT, model estimates

Model	STRUCT_1	STRUCT_2	STRUCT_3
Estimation			
– dependent variable	$\Delta_2\ln(struct_t)$	$\Delta_2\ln(struct_t)$	$\Delta_2\ln(struct_t)$
– observations	29	29	29
– method	LS	LS	LS
Variable coefficients			
– constant	-0.180	-0.174	-0.169
– d1	0.161	0.241	0.161
– d2	0.341	0.277	0.345
– d3	0.213	0.178	0.229
– $\Delta\ln(hc_t)$	–	0.628	–
– $\Delta_2\ln(struct_{t-1})$	-0.585	-0.671	-0.576
– $\Delta\ln(trans_t)$	–	–	-1.660 **a**
Model fit			
– Adj. R-squared	0.77	0.85	0.79
– AIC	-2.52	-2.92	-2.59
– SC	-2.28	-2.63	-2.31

Note: Results are for models estimated over the training period (March 2002 to December 2012). All estimates are significant at the 5 per cent level unless otherwise specified. **a** Insignificant at the 5 per cent level but significant at the 10 per cent level. **b** Insignificant at the 10 per cent level.
Source: ABARES estimates

Table B9 STRUCT, out-of-sample forecasting performance

Error measure	Forecast time horizon	STRUCT_1 a	STRUCT_2	STRUCT_3
RMSE	One-quarter-ahead	21 826	22 501	22 702
	Two-quarters-ahead	33 978	34 017	36 801
	Three-quarters-ahead	32 092	41 355	43 856
	Four-quarters-ahead	46 572	61 077	63 612
	Average **b**	47 229	57 927	65 530
	Total sales over year ahead	110 220	139 738	154 814
MAPE (%)	One-quarter-ahead	7.7	6.9	8.2
	Two-quarters-ahead	10.8	9.8	12.5
	Three-quarters-ahead	10.2	11.6	13.8
	Four-quarters-ahead	12.6	15.9	17.7
	Average **b**	7.2	7.8	10.3
	Total sales over year ahead	7.2	8.5	11.0
Directional accuracy (%)	One-quarter-ahead	83	92	58
	Two-quarters-ahead	82	91	82
	Three-quarters-ahead	60	70	60
	Four-quarters-ahead	44	33	33
	Average **c**	67	71	58
	Total sales over year ahead	78	44	56

Note: Results are for models estimated over the training period (March 2002 to December 2012). A lower RMSE or MAPE indicates more accurate point forecasts over the validation period. **a** Preferred model. **b** Average forecast errors across all rolling forecasts estimated over the validation period. **c** Average directional accuracy across all rolling forecasts estimated over the validation period.
Source: ABARES estimates

UNTREAT

Candidate models

Table B10 presents estimation results for seven candidate single equation models of total untreated pine sales identified as having suitable in-sample properties. All candidate models assume that the untreated pine sales series contains a single unit root and estimates the change in the natural logarithm of sales. Key explanatory variables include changes in house and other residential commencements, sawmill input costs, road transport costs and the NZ/Australian dollar exchange rate. All models except UNTREAT_5 and UNTREAT_6 include moving average processes, and UNTREAT_2 and UNTREAT_4 include a time trend. An observational dummy for December 2002 was found to be statistically significant in models 2, 3 and 7.

Out-of-sample forecasting performance

Table B11 summarises the out-of-sample forecasting performance of the seven single equation models of total untreated pine sales. While UNTREAT_4 and UNTREAT_7 generated the most accurate three- and four-quarters-ahead forecasts, UNTREAT_2 generated the most accurate one- and two-quarters-ahead forecasts, and had the lowest average forecast error over the validation period. UNTREAT_2 was also the most accurate predictor of the direction of sales over most time horizons. For these reasons, UNTREAT_2 is the preferred model for total untreated pine sales.

Table B10 UNTREAT, model estimates

Model	UNTREAT_1	UNTREAT_2	UNTREAT_3	UNTREAT_4	UNTREAT_5	UNTREAT_6	UNTREAT_7
Estimation							
– dependent variable	$\Delta\ln(untreat_t)$	$\Delta\ln(untreat_t)$	$\Delta\ln(untreat_t)$	$\Delta\ln(untreat_t)$	$\Delta\ln(untreat_t)$	$\Delta\ln(untreat_t)$	$\Delta\ln(untreat_t)$
– observations	43	43	43	43	43	43	43
– method	ARMA ML	LS	ARMA ML	LS	LS	LS	ARMA ML
Variable coefficients							
– constant	-0.073	-0.065	-0.077	-0.063	0.429	0.509	0.390
– d_1	0.114 **a**	0.154	0.125	0.153	0.119	0.108	0.134
– d_2	0.097	0.115	0.097	0.114	0.115	0.122	0.133
– d_3	0.094	0.116	0.088	0.114	0.107	0.118	0.129
– trend	–	-0.001	–	-0.001	–	–	–
– $\Delta\ln(hc_t)$	0.588	0.667	0.548	0.599	0.537	0.478	0.543
– $\Delta\ln(oc_t)$	–	–	0.123 **a**	0.101 **a**	–	–	–
– $\ln(smc_t)$	–	–	–	–	-0.117	-0.132	-0.110
– $\Delta\ln(trans_t)$	–	–	–	–	–	-1.406 **a**	-1.037 **a**
– $\Delta\ln(er\_nz_t)$	–	-0.439 **a**	-0.406 **a**	-0.503	-0.554 **a**	-0.537 **a**	-0.538
– MA(1)	–	–	–	–	–	–	-0.460
– MA (4)	0.577	–	0.707	–	–	–	–
– outlier_2002q4	–	0.191	–	0.176	–	–	0.195
Model fit							
– Adj. R-squared	0.664	0.771	0.742	0.784	0.690	0.71	0.83
– AIC	-2.705	-3.105	-2.904	-3.145	-2.822	-2.88	-3.33
– SC	-2.418	-2.778	-2.535	-2.776	-2.536	-2.55	-2.88

Note: Results are for models estimated over the training period (March 2002 to December 2012). All estimates are significant at the 5 per cent level unless otherwise specified. **a** Insignificant at the 5 per cent level but significant at the 10 per cent level. **b** Insignificant at the 10 per cent level.
Source: ABARES estimates

Table B11 UNTREAT, out-of-sample forecasting performance

Error measure	Forecast time horizon	UNTREAT_1	UNTREAT_2 a	UNTREAT_3	UNTREAT_4	UNTREAT_5	UNTREAT_6	UNTREAT_7
RMSE	One-quarter-ahead	7 982	4 579	10 272	5 565	5 282	5 873	6 244
	Two-quarters-ahead	10 780	7 911	11 501	8 529	9 215	9 634	9 490
	Three-quarters-ahead	11 547	11 039	12 127	10 925	12 397	12 978	12 026
	Four-quarters-ahead	15 868	14 771	19 097	14 374	15 388	14 948	13 585
	Average **b**	18 024	15 357	21 108	15 363	16 670	17 545	16 387
	Total sales over year ahead	41 282	36 266	47 783	35 649	39 253	41 517	39 267
MAPE (%)	One-quarter-ahead	5.0	2.5	6.3	3.0	3.0	3.3	3.7
	Two-quarters-ahead	5.9	4.0	6.5	3.9	5.0	4.7	5.2
	Three-quarters-ahead	6.2	5.6	5.8	5.2	6.5	5.9	6.2
	Four-quarters-ahead	7.5	7.1	8.5	6.6	7.7	7.0	6.6
	Average **b**	4.9	3.7	5.5	3.5	4.3	4.2	4.3
	Total sales over year ahead	4.7	4.1	5.3	3.7	4.6	4.2	4.5
Directional accuracy (%)	One-quarter-ahead	83	100	58	92	92	92	92
	Two-quarters-ahead	91	100	73	100	91	91	91
	Three-quarters-ahead	90	100	70	80	90	90	90
	Four-quarters-ahead	78	100	67	100	89	78	89
	Average **c**	86	100	67	93	90	88	90
	Total sales over year ahead	56	44	67	44	67	33	56

Note: Results are for models estimated over the training period (March 2002 to December 2012). A lower RMSE or MAPE indicates more accurate point forecasts over the validation period. **a** Preferred model. **b** Average forecast errors across all rolling forecasts estimated over the validation period. **c** Average directional accuracy across all rolling forecasts estimated over the validation period.
Source: ABARES estimates

Models of the ratio of two series

RATIO_STRUC

Candidate models

Table B12 presents estimation results for two candidate single equation models describing the share of treated pine as a proportion of total structural pine sales. RATIO_STRUCT_1 estimates the change in the share of treated pine as a proportion of total structural pine sales. RATIO_STRUCT_2 estimates the change in the natural logarithm of the share. No models estimating the annual change in share were found to have suitable in-sample properties and no explanatory variables or ARMA terms were found to be statistically significant in any of the models.

Table B12 RATIO_STRUCT, model estimates

Model	RATIO_STRUCT_1	RATIO_ STRUCT_2
Estimation		
– dependent variable	$\Delta treat\_share_t$	$\Delta \ln(treat\_share_t)$
– observations	31	31
– method	LS	LS
Variable coefficients		
– constant	0.008	0.041
– outlier_2005q3	–	0.308
Model fit		
– Adj. R-squared	0.00	0.46
– AIC	-6.49	-2.75
– SC	-6.44	-2.66

Note: Results are for models estimated over the training period (March 2002 to December 2012). All estimates are significant at the 5 per cent level unless otherwise specified. **a** Insignificant at the 5 per cent level but significant at the 10 per cent level. **b** Insignificant at the 10 per cent level.
Source: ABARES estimates

Out-of-sample forecasting performance

Table B13 presents a summary of the out-of-sample forecasting performance of the two candidate models of the share of treated pine as a proportion of total structural pine sales. RATIO_STRUCT_1 generated the most accurate forecasts over all time horizons. It is therefore the preferred model for the share of category 2 sales as a proportion of total untreated pine sales.

Table B13 RATIO_STRUCT, out-of-sample forecasting performance

Error measure	Forecast time horizon	RATIO_ STRUCT_1 a	RATIO_ STRUCT_2
RMSE	One-quarter-ahead	0.012	0.013
	Two-quarters-ahead	0.013	0.018
	Three-quarters-ahead	0.011	0.022
	Four-quarters-ahead	0.012	0.028
	Average **b**	0.020	0.031
MAPE (%)	One-quarter-ahead	3.8	4.7
	Two-quarters-ahead	4.5	4.7
	Three-quarters-ahead	2.7	5.9
	Four-quarters-ahead	2.5	7.3
	Average **b**	2.8	4.3
Directional accuracy (%)	One-quarter-ahead	58	58
	Two-quarters-ahead	45	55
	Three-quarters-ahead	40	40
	Four-quarters-ahead	56	56
	Average **c**	50	52

Note: Results are for models estimated over the training period (March 2002 to December 2012). A lower RMSE or MAPE indicates more accurate point forecasts over the validation period. Forecasting errors for total sales over the year ahead were not calculated because they also depend on forecasts of actual sales of treated or untreated structural pine.
a Preferred model. **b** Average forecast errors across all rolling forecasts estimated over the validation period. **c** Average directional accuracy across all rolling forecasts.
Source: ABARES estimates

RATIO_UNTREAT

Candidate models

Table B14 presents estimation results for the two single equation models describing the share of category 2 sales as a proportion of total untreated pine sales. The candidate models are pure time series models in that the only explanatory variables are the past values of sales and past predictions of sales.

Out-of-sample forecasting performance

Table B15 presents a summary of the out-of-sample forecasting performance of the two single equation models for the share of treated pine as a proportion of total structural pine sales. Estimates of the share of category 2 sales as a proportion of total untreated pine sales over a one-year time horizon cannot be estimated using the candidate models alone. For this reason, the corresponding errors are not presented. While RATIO_UNTREAT_2 generated the most accurate one-quarter-ahead forecasts, the RMSE was only marginally smaller than that for RATIO_UNTREAT_1, which generated the most accurate forecasts over all other time horizons and had the smallest average error over the validation period. For these reasons, RATIO_UNTREAT_1 is the preferred approach to forecasting the share of category 2 sales as a proportion of total untreated pine sales.

Table B14 RATIO_UNTREAT, model estimates

Model	RATIO_UNTREAT_1	RATIO_UNTREAT_2	RATIO_UNTREAT_2
Estimation			
– dependent variable	Δ(cat2_share$_t$)	Δ(cat2_share$_t$)	Δ(cat2_share$_t$)
– observations	42	41	42
– method	ARMA	LS	LS
Variable coefficients			
– constant	0.000 **b**	0.001 **b**	0.001 **b**
– Δ(split$_{t-1}$)	–	-0.451	-0.303
– Δ(split$_{t-2}$)	–	-0.261 **a**	-0.247 **a**
– MA(1)	-0.633	–	–
– outlier_2004q1	–	-0.020	-0.020
– outlier_2009q1	–	–	-0.020
Model fit			
– Adj. R-squared	0.22	0.24	0.29
– AIC	-6.45	-6.43	-6.52
– SC	-6.33	-6.26	-6.36

Note: Results are for models estimated over the training period (March 2002 to December 2012). Coefficient estimates of differ from those of the most up-to-date version of the model presented in Section 4. All estimates are significant at the 5 per cent level unless otherwise specified. **a** Insignificant at the 5 per cent level but significant at the 10 per cent level. **b** Insignificant at the 10 per cent level.
Source: ABARES estimates

Table B15 RATIO_ UNTREAT, out-of-sample forecasting performance

Error measure	Forecast time horizon	RATIO_UNTREAT_1 a	RATIO_UNTREAT_2	RATIO_UNTREAT_3
RMSE	One-quarter-ahead	0.007	0.007	0.007
	Two-quarters-ahead	0.008	0.009	0.009
	Three-quarters-ahead	0.009	0.009	0.010
	Four-quarters-ahead	0.010	0.010	0.012
	Average **b**	0.011	0.012	0.027
MAPE (%)	One-quarter-ahead	9.1	9.6	10.1
	Two-quarters-ahead	10.4	10.9	11.6
	Three-quarters-ahead	10.2	10.7	12.1
	Four-quarters-ahead	9.4	9.0	10.9
	Average **b**	6.4	6.7	7.7
Directional accuracy (%)	One-quarter-ahead	50	33	42
	Two-quarters-ahead	36	45	45
	Three-quarters-ahead	40	40	50
	Four-quarters-ahead	33	56	44
	Average **c**	40	44	45

Note: Results are for models estimated over the training period (March 2002 to December 2012). A lower RMSE or MAPE indicates more accurate point forecasts over the validation period. Forecasting errors for total sales over the year ahead were not calculated because they also depend on forecasts of actual sales of category 1 or category 2 untreated pine. **a** Preferred model. **b** Average forecast errors across all rolling forecasts estimated over the validation period. **c** Average directional accuracy across all rolling forecasts.
Source: ABARES estimates

Vector error correction models

VEC_STRUCT

Candidate models

Table B16 presents estimation results for the three vector error correction models of total untreated pine and treated pine sales. In these models, deviations from a steady state equilibrium relationship between the variables of interest help to explain short-run movements. Key explanatory variables include house commencements, the NZ/Australian dollar exchange rate and sawmill inputs costs.

Table B16 VEC_STRUCT, model estimates

Model	VEC_STRUCT1		VEC_STRUCT2		VEC_STRUCT3	
Estimation						
– dependent variable	$\Delta\ln(untreat_t)$	$\Delta\ln(treat_t)$	$\Delta\ln(untreat_t)$	$\Delta\ln(treat_t)$	$\Delta\ln(untreat_t)$	$\Delta\ln(treat_t)$
– observations	31	31	31	31	31	31
Cointegrating equation coefficients						
– ln $(untreat_t)$		1.000		1.000		1.000
– ln $(treat_t)$		-2.33		-2.70		-2.09
		[-7.54]		[-7.17]		[-7.32]
– constant		11.821		15.85		9.02
– trend		0.049		0.052		0.052
		[4.28]		[3.76]		[3.99]
VAR coefficients						
– speed of adjustment	-0.009 **b**	-0.127	0.012 **b**	0.105	-0.004 **b**	0.132
– constant	-0.109	-0.036	-0.111	-0.035	0.386 **b**	0.489 **b**
– d_1	0.135	0.153	0.157	0.153	0.158	0.156
– d_2	0.128	0.085	0.129	0.083	0.133	0.088
– d_3	0.118	0.150	0.111	0.149	0.113	0.150
– $\Delta\ln(hc_t)$	0.458	0.698	0.535	0.703	0.528	0.697
– $\Delta\ln(er\_nz_t)$	–	–	-0.468 **a**	-0.039 **b**	-0.482	-0.060 **b**
– $\ln(smc_t)$	–	–	–	–	-0.111 **a**	-0.117 **a**
– outlier_2005q2	0.057	-0.321[a]	0.029	-0.325	0.031 **b**	-0.327
– outlier_2008q3	-0.057	-0.133[a]	-0.034	-0.129	-0.047 **b**	-0.141
Model fit						
– Adj. R-squared	0.77	0.88	0.79	0.88	0.81	0.88
– AIC	-6.37	-6.37	-6.42	-6.42	-6.46	-6.46
– SC	-5.50	-5.50	-5.45	-5.45	-5.40	-5.40

Note: Results are for models estimated over the training period (March 2002 to December 2012). All estimates are significant at the 5 per cent level unless otherwise specified. Statistical significance of VAR coefficients is based on Student's t-distribution. Figures in square brackets are t-statistics for coefficients in cointegrating equations. **a** Insignificant at the 5 per cent level but significant at the 10 per level. **b** Insignificant at the 10 per cent level.
Source: ABARES estimates

All models include a trend in the cointegrating equation given the linear trend in share of treated pine as a proportion of total structural pine sales over time (Figure 2). The estimated parameters of the cointegrating equations indicate that treated pine sales and total untreated pine sales move together in the long run. This is counter to the hypothesis that treated and untreated pine products are substitutes. The speed of adjustment parameters for treated pine were significant in all three models, but the opposite was true of total untreated pine. The model estimates, therefore, suggest that deviations from the steady-state equilibrium are corrected through adjustments in sales of treated pine only.

Out-of-sample forecasting performance

Table B17 presents a summary of the out-of-sample forecasting performance of the three vector error correction models of treated and total untreated pine sales. Forecast errors and directional accuracy are presented for untreated and treated sales, individually and combined. VEC_STRUCT_1 generated the most accurate one-, two- and three-quarters ahead forecasts. VEC_STRUCT_2 generated the most accurate forecasts of untreated pine over all time horizons. More importantly, VEC_STRUCT_2 generated the most accurate forecasts over all time horizons for the average of both series. For these reasons, VEC_STRUCT_2 is the preferred vector error correction model for untreated and treated pine sales.

VEC_UNTREAT

Candidate models

Table B18 presents estimation results for three vector error correction models of category 1 and category 2 untreated pine sales. All models include only a constant in the trend given the lack of trend in the share of category 2 sales as a proportion of total untreated pine sales (Figure 2).

The estimated parameters of the cointegrating equations of both models imply that sales of category 1 and category 2 untreated pine tend to move in the same direction in the long run. This is consistent with the two products being complements. However, the ratio of category 1 to category 2 untreated pine sales increases as sales of total untreated pine increase. The speed of adjustment parameters are significant for category 2 untreated pine only, suggesting that deviations from the long-run equilibrium relationship are corrected through adjustment of sales of category 2 untreated pine.

Out-of-sample forecasting performance

Table B19 presents a summary of the out-of-sample forecasting performance of the three vector error correction models of category 1 and category 2 untreated pine sales. Forecast errors and directional accuracy are presented for category 1 and category 2 sales, individually and combined. Focusing on the average forecasts error across the two series, VEC_UNTREAT_2 generated the most accurate one- and two-quarters-ahead forecasts. VEC_UNTREAT_1 generated the most accurate three- and four-quarters-ahead forecasts. VEC_UNTREAT_1 also had the lowest average forecast error over the validation period for the two series combined. For these reasons, VEC_UNTREAT_1 is the preferred vector error correction model for category 1 and category 2 sales.

Table B17 VEC_STRUCT, out-of-sample forecasting performance

Error measure	Forecast time horizon	UNTREAT			TREAT			AVERAGE d		
		VEC1	**VEC2 a**	**VEC3**	**VEC1**	**VEC2 a**	**VEC3**	**VEC1**	**VEC2 a**	**VEC3**
RMSE	One-quarter-ahead	4 621	4 225	5 589	8 531	8 578	8 976	6 860	6 761	7 477
	Two-quarters-ahead	6 655	6 178	9 278	9 960	10 221	11 362	8 470	8 445	10 372
	Three-quarters-ahead	7 935	6 882	11 873	8 826	8 935	11 321	8 392	7 975	11 600
	Four-quarters-ahead	10 306	7 292	15 183	10 476	9 922[b]	13 414	10 391	8 707	14 326
	Average **b**	11 618	9 572	16 224	11 736	11 421	13 868	11 677	10 537	15 092
	Total sales over year ahead	26 932	23 035	38 550	23 223	22 107	28 340	25 146	22 576	33 832
MAPE (%)	One-quarter-ahead	2.8	2.3	3.3	7.1	7.3	7.4	5.0	4.8	5.4
	Two-quarters-ahead	3.8	3.1	5.1	7.4	7.7	8.1	5.6	5.4	6.6
	Three-quarters-ahead	3.9	3.2	6.3	6.5	6.5	8.7	5.2	4.9	7.5
	Four-quarters-ahead	4.6	3.4	7.6	7.2	6.6	8.9	5.9	5.0	8.3
	Average **b**	3.0	2.3	4.2	4.8	4.8	5.6	3.9	3.6	4.9
	Total sales over year ahead	3.3	2.6	4.7	4.2	4.1	4.6	3.8	3.4	4.7
Directional accuracy (%)	One-quarter-ahead	100	100	100	75	75	75	88	88	88
	Two-quarters-ahead	100	100	100	82	82	82	91	91	91
	Three-quarters-ahead	100	100	100	60	60	60	80	80	80
	Four-quarters-ahead	89	89	89	67	67	67	78	78	78
	Average **c**	97	97	97	71	71	71	84	84	84
	Total sales over year ahead	67	56	44	100	100	100	83	78	72

Note: VEC1, VEC2 and VEC3 refer to VEC_STRUCT1, VEC_STRUCT2 and VEC_STRUCT3, respectively. Results are for models estimated over the training period (March 2002 to December 2012). A lower RMSE or MAPE indicates more accurate point forecasts over the validation period. Forecasting errors for total sales over the year ahead were not calculated because they also depend on forecasts of actual sales of category 1 or category 2 untreated pine. **a** Preferred model. **b** Average forecast errors across all rolling forecasts estimated over the validation period. **c** Average directional accuracy across all rolling forecasts estimated over the validation period. **d** Average of forecast errors for category 1 and category 2 untreated pine series.
Source: ABARES estimates

Table B18 VEC_UNTREAT, model estimates

Model	VEC_UNTREAT1		VEC_UNTREAT2		VEC_UNTREAT2	
Estimation						
– dependent variable	Δln($cat1_t$)	Δln($cat2_t$)	Δln($cat1_t$)	Δln($cat2_t$)	Δln($cat1_t$)	Δln($cat2_t$)
– observations	42	42	43	43	43	43
Cointegrating equation coefficients						
– ln($cat1_t$)		1.000		1.000		1.000
– ln($cat2_t$)		-0.883		-0.852		-0.693
		[-9.560]		[-8.994]		[-12.71]
– constant		-3.381		-3.701		-5.34
VAR coefficients						
– speed of adjustment	0.111 **b**	0.641	0.097 **b**	0.626	0.163 **b**	0.892
– constant	-0.105	-0.081	-0.107	-0.086	0.719	-1.047
– d_1	0.159	0.129	0.168	0.147	0.157	0.182
– d_2	0.115	0.133	0.120	0.141	0.110	0.164
– d_3	0.098	0.120	0.126	0.094	0.110	0.113
– Δln(hc_t)	0.643	0.470 **a**	0.671	0.526	0.683	0.610
– Δln(ex_nz_t)	–	–	-0.414 **b**	-0.715 **b**	-0.503	-0.813
– ln(smc_t)	–	–	–	–	-0.185	0.213
– outlier_2002q4	0.213	0.088 **a**	0.210	0.087 **b**	0.212	0.130 **b**
– outlier_2004q1	-0.017 **a**	-0.392	-0.023 **b**	0.404	-0.056 **b**	-0.369
Model fit						
– Adj. R-squared	0.73	0.64	0.74	0.67	0.79	0.65
– AIC	-4.88	-4.88	-4.81	-4.81	-5.07	-5.07
– SC	-4.05	-4.05	-3.99	-3.99	-4.16	-4.16

Note: Results are for models estimated over the training period (March 2002 to December 2012). All estimates are significant at the 5 per cent level unless otherwise specified. Statistical significance of VAR coefficients is based on Student's t-distribution. Figures in square brackets are t-statistics for coefficients in cointegrating equations. **a** Insignificant at 5 the per cent level but significant at the 10 per cent level. **b** Insignificant at the 10 per cent level.
Source: ABARES estimates

Table B19 VEC_UNTREAT, out-of-sample forecasting performance

Error measure	Forecast time horizon	CAT1			CAT2			AVERAGE d		
		VEC1 a	**VEC2**	**VEC3**	**VEC1 a**	**VEC2**	**VEC3**	**VEC1 a**	**VEC2**	**VEC3**
RMSE	One-quarter-ahead	5 342	4 824	6 502	1 360	1 433	1 486	3 898	3 558	4 716
	Two-quarters-ahead	8 210	8 013	10 434	1 961	2 015	1 740	5 969	5 842	7 480
	Three-quarters-ahead	8 613	10 198	13 350	2 475	2 603	1 912	6 337	7 442	9 536
	Four-quarters-ahead	9 281	11 532	16 548	2 820	3 099	1 950	6 859	8 444	11 782
	Average **b**	11 607	13 650	17 635	2 889	3 316	2 462	8 458	9 933	12 591
	Total sales over year ahead	26 848	33 327	42 871	6 164	7 112	4 835	19 478	24 096	30 507
MAPE (%)	One-quarter-ahead	3.6	3.1	4.4	9.3	10.0	9.7	6.5	6.6	7.1
	Two-quarters-ahead	4.8	4.9	6.9	12.4	13.5	11.3	8.6	9.2	9.1
	Three-quarters-ahead	5.0	5.8	8.0	14.6	15.8	11.8	9.8	10.8	9.9
	Four-quarters-ahead	4.4	6.0	9.0	15.7	17.2	10.0	10.1	11.6	9.5
	Average **b**	3.3	3.9	5.3	8.4	9.9	7.2	5.9	6.9	6.3
	Total sales over year ahead	3.1	4.2	5.8	8.3	9.4	6.3	5.7	6.8	6.1
Directional accuracy (%)	One-quarter-ahead	100	100	100	92	92	92	96	96	96
	Two-quarters-ahead	100	100	100	91	8	82	95	91	91
	Three-quarters-ahead	90	90	100	90	90	90	90	90	95
	Four-quarters-ahead	89	89	100	56	56	56	73	73	78
	Average **c**	95	95	100	82	80	80	88	87	90
	Total sales over year ahead	67	67	44	56	33	33	61	50	39

Note: VEC1, VEC2 and VEC3 refer to VEC_UNTREAT1, VEC_UNTREAT2 and VEC_UNTREAT3, respectively. Results are for models estimated over the training period (March 2002 to December 2012). A lower RMSE or MAPE indicates more accurate point forecasts over the validation period. Forecasting errors for total sales over the year ahead were not calculated because they also depend on forecasts of actual sales of category 1 or category 2 untreated pine. **a** Preferred model. **b** Average forecast errors across all rolling forecasts estimated over the validation period. **c** Average directional accuracy across all rolling forecasts estimated over the validation period. **d** Average of forecast errors for category 1 and category 2 untreated pine series.
Source: ABARES estimates

Appendix C: Assessing combinations of models

This appendix presents estimates of the out-of-sample forecasting performance of the 18 combinations of models (Table 3) and discusses the basis for selecting Combination_3 as the preferred combination of models for forecasting the four series.

Table C1 shows the calculations used to generate forecasts for each of the four sales series for each combination of models while Table C2, Table C3 and Table C4 present estimates of RMSE, directional forecasting accuracy, and MAPE for the three structural pine series and averages.

Results for landscape wood products are not included in the tables or calculation of the averages because the same model was used in all cases and had no effect on the ranking of the various combinations of other models.

Based on the estimates of point forecasting accuracy presented in Table C2 the four best combinations of models are Combination_3, Combination_5, Combination_7 and Combination_10. These four combinations of models generated the most accurate point forecasts in one or more instances.

Combination_10 generated the most accurate forecasts of category 1 untreated pine sales over all time horizons by combining simultaneous forecasts of treated pine and total untreated pine (using VEC_STRUCT_2) with forecasts of the share of category 2 sales as a proportion of total untreated pine (using RATIO_UNTREAT_1).

Combination_7 generated the most accurate forecasts of category 2 untreated pine and treated pine sales over all time horizons. This was achieved by combining forecasts of total treated pine sales (using TREAT_1) with forecasts of the share of treated pine sales as a proportion of total structural pine sales (using RATIO_STRUCT_1) and forecasts of the share of category 2 sales in total untreated pine sales (using RATIO_UNTREAT_1).

Combination_3 and Combination_5 also generated the most accurate forecasts of category 1 sales. Combination_3 used forecasts of treated pine sales (using TREAT1), category 1 untreated pine sales (using CAT1_1) and the share of category 2 sales as a proportion of total untreated pine sales (using UNTREAT6). Combination_5 used forecasts of treated pine (using TREAT1), the share of treated pine as a proportion of total structural pine (using RATIO_STRUCT1) and the share of category 2 sales in total untreated pine sales (using RATIO_UNTREAT1). As a result, both combinations generated less accurate forecasts of category 1 sales than Combination_10, and less accurate forecasts of category 2 sales than Combination_7.

However, taking the average forecast error across the three structural pine series (Table C2), Combination_7 generated the most accurate one-quarter-ahead forecasts, Combination_5 generated the most accurate three- and four-quarters-ahead forecasts, and Combination_3 generated the most accurate two-quarters-ahead and one-year-ahead forecasts. Combination_3 also had the lowest average forecast error over the validation period and across the three structural pine series. With priority given to point forecasting accuracy over directional accuracy, and taking into consideration performance across all of the sales series, Combination_3 is the preferred combination of models.

Table C1 Calculation of structural pine series based on multiple models

Model combination	Calculation of landscape wood products sales	Calculation of treated pine sales
1	LNDSCP	TREAT
2	LNDSCP	TREAT
3	LNDSCP	TREAT
4	LNDSCP	TREAT
5	LNDSCP	TREAT
6	LNDSCP	TREAT
7	LNDSCP	TREAT
8	LNDSCP	STRUCT-UNTREAT
9	LNDSCP	$\frac{\text{UNTREAT*RATIO\_STRUCT}}{\text{(1-RATIO\_STRUCT)}}$
10	LNDSCP	VEC_STRUCT
11	LNDSCP	STRUCT-UNTREAT
12	LNDSCP	$\frac{\text{UNTREAT*RATIO\_STRUCT}}{\text{(1-RATIO\_STRUCT)}}$
13	LNDSCP	STRUCT*RATIO_STRUCT
14	LNDSCP	$\text{CAT1*}\left(1+\frac{\text{RATIO\_UNTREAT}}{\text{1-RATIO\_UNTREAT}}\right)*\left(\frac{\text{RATIO\_STRUCT}}{\text{1-RATIO\_STRUCT}}\right)$
15	LNDSCP	VEC_STRUCT
16	LNDSCP	STRUCT*RATIO_STRUCT
17	LNDSCP	STRUCT-VEC_UNTREAT
18	LNDSCP	VEC_UNTREAT*RATIO_STRUCT*(1-RATIO_STRUCT)

Note: Each column shows how forecasts from the various econometric models are combined to generate forecasts for the specified sales series.

Table C1 Calculation of structural pine series based on multiple models *continued*

Model combination	Calculation of category 1 untreated pine sales	Calculation of category 2 untreated pine sales
1	CAT1	UNTREAT-CAT1
2	CAT1	STRUCT-TREAT-CAT1
3	CAT1	$\frac{\text{CAT1*RATIO\_UNTREAT}}{\text{(1-RATIO\_UNTREAT)}}$
4	(STRUCT-TREAT)*(1-RATIO_UNTREAT)	(STRUCT-TREAT)*RATIO_UNTREAT
5	$\frac{\text{TREAT*(1-RATIO\_STRUCT)}}{\text{RATIO\_STRUCT*(1-RATIO\_UNTREAT)}}$	$\frac{\text{TREAT*(1-RATIO\_STRUCT)}}{\text{RATIO\_STRUCT*RATIO\_UNTREAT}}$
6	VEC_UNTREAT	VEC_UNTREAT
7	UNTREAT*(1-RATIO_UNTREAT)	UNTREAT*RATIO_UNTREAT
8	UNTREAT*(1-RATIO_UNTREAT)	UNTREAT*RATIO_UNTREAT
9	UNTREAT*(1-RATIO_UNTREAT)	UNTREAT*RATIO_UNTREAT
10	VEC_STRUCT*(1-RATIO_UNTREAT)	VEC_STRUCT*RATIO_UNTREAT
11	CAT1	UNTREAT-CAT1
12	CAT1	UNTREAT-CAT1
13	CAT1	STRUCT-(1-RATIO_STRUCT)-CAT1
14	CAT1	$\frac{\text{CAT1*RATIO\_UNTREAT}}{\text{(1-RATIO\_UNTREAT)}}$
15	CAT1	VEC_STRUCT-CAT1
16	STRUCT*(1-RATIO_STRUCT)*(1-RATIO_UNTREAT)	STRUCT*(1-RATIO_STRUCT)*RATIO_UNTREAT
17	VEC_UNTREAT	VEC_UNTREAT
18	VEC_UNTREAT	VEC_UNTREAT

Note: Each column shows how forecasts from the various econometric models are combined to generate forecasts for the specified sales series.

Table C2 RMSE of various combinations of models

Sales series	**Time horizon**	**Model combination**												
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Treated pine sales	One-quarter-ahead	5 716	5 716	5 716	5 716	5 716	5 716	5 716	17 332	8 876	8578	17 332	8 876	10 118
	Two-quarters-ahead	7 835	7 835	7 835	7 835	7 835	7 835	7 835	28 386	12 300	10221	28 386	12 300	15 706
	Three-quarters-ahead	7 494	7 494	7 494	7 494	7 494	7 494	7 494	34 240	11 578	8935	34 240	11 578	13 647
	Four-quarters-ahead	8 411	8 411	8 411	8 411	8 411	8 411	8 411	47 916	14 567	9922	47 916	14 567	18 562
	Average **b**	8 310	8 310	8 310	8 310	8 310	8 310	8 310	50 568	14 026	11421	50 568	14 026	20 122
	Total sales over year ahead	15 893	15 893	15 893	15 893	15 893	15 893	15 893	120 735	28 661	22 107	120 735	28 661	45 635
Category 1 sales	One-quarter-ahead	5 174	5 174	5 174	14 538	6 089	5 342	5 048	5 048	5 048	4 243	5 174	5 174	5 174
	Two-quarters-ahead	7 414	7 414	7 414	22 502	7 961	8 210	8 023	8 023	8 023	5 754	7 414	7 414	7 414
	Three-quarters-ahead	7 658	7 658	7 658	2 7217	7 127	8 613	10 822	10 822	10 822	6 081	7 658	7 658	7 658
	Four-quarters-ahead	8 588	8 588	8 588	39 687	6 604	9 281	14 460	14 460	14 460	6 404	8 588	8 588	8 588
	Average **b**	10 592	10 592	10 592	41 202	11 270	11 607	14 894	14 894	14 894	8 357	10 592	10 592	10 592
	Total sales over year ahead	23 611	23 611	23 611	97 293	25 565	26 848	35 330	35 330	35 330	20 121	23 611	23 611	23 611
Category 2 sales	One-quarter-ahead	5 854	13 959	1 354	1 440	1 552	1360	1194	1194	1194	7882	5 854	5 854	8 709
	Two-quarters-ahead	11 179	20 242	1 880	1 921	2 010	1961	1468	1468	1468	7611	11 179	11 179	11 598
	Three-quarters-ahead	15 686	25 228	2 310	2 893	2 002	2475	1628	1628	1628	7346	15 686	15 686	15 457
	Four-quarters-ahead	20 441	39 420	2 589	4 342	2 008	2820	1668	1668	1668	7053	20 441	20 441	24 663
	Average **b**	21 257	39 661	2 809	4 106	2 592	2889	2172	2172	2172	11942	21 257	21 257	24 541
	Total sales over year ahead	50 276	94 178	6 199	9 288	4 899	6 164	4 133	4 133	4 133	31325	50 276	50 276	57 949
Average **a**	One-quarter-ahead	5 589	9 207	4 520	9 057	4 904	4 585	4 456	10 445	5 935	7 158	10 976	6 827	8 266
	Two-quarters-ahead	8 969	13 242	6 322	13 801	6 552	6 649	6 530	17 052	8 521	8 073	18 126	10 508	12 058
	Three-quarters-ahead	10 967	15 825	6 328	16 384	6 082	6 745	7 658	20 754	9 198	7 545	22 189	12 093	12 699
	Four-quarters-ahead	13 691	23 794	7 099	23 556	6 282	7 412	9 706	28 912	11 889	7 941	30 482	15 317	18 498
	Average **b**	14 527	24 181	7 940	24 382	8 221	8 409	9 926	30 461	11 878	10 691	32 255	15 925	19 316
	Total sales over year ahead	33 355	56 802	16 818	57 168	17 609	18 361	22 494	72 669	26 374	24 999	76 729	36 086	44 715

Note: Results are for models estimated over the training period (March 2002 to December 2012). **a** Average RMSE across all three structural pine series. **b** Average forecast errors across all rolling forecasts estimated over the validation period.
Source: ABARES estimates

Table C2 RMSE of various combinations of models *continued*

Sales series	**Time horizon**	**Model combination**				
		14	**15**	**16**	**17**	**18**
Treated pine sales	One-quarter-ahead	7 999	8 578	10 118	16 571	8 022
	Two-quarters-ahead	10 766	10 221	15 706	25 800	11 041
	Three-quarters-ahead	8 342	8 935	13 647	26 966	8 782
	Four-quarters-ahead	8 513	9 922	18 562	40 042	9 774
	Average **b**	11 197	11 421	20 122	41 070	12 377
	Total sales over year ahead	22 050	22 107	45 635	96 063	26 309
Category 1 sales	One-quarter-ahead	5 174	5 174	9 484	5 342	5 342
	Two-quarters-ahead	7 414	7 414	14 147	8 210	8 210
	Three-quarters-ahead	7 658	7 658	17 928	8 613	8 613
	Four-quarters-ahead	8 588	8 588	26 162	9 281	9 281
	Average **b**	10 592	10 592	27 185	11 607	11 607
	Total sales over year ahead	23 611	23 611	64 201	26 848	26 848
Category 2 sales	One-quarter-ahead	1 354	4 020	1 274	1 360	1 360
	Two-quarters-ahead	1 880	6 852	1 517	1 961	1 961
	Three-quarters-ahead	2 310	9 048	2 176	2 475	2 475
	Four-quarters-ahead	2 589	11 537	3 091	2 820	2 820
	Average **b**	2 809	12 891	2 949	2 889	2 889
	Total sales over year ahead	6 199	30 596	6 264	6 164	6 164
Average **a**	One-quarter-ahead	5 555	6 232	8 040	10 083	5 620
	Two-quarters-ahead	7 625	8 294	12 236	15 672	8 024
	Three-quarters-ahead	6 673	8 570	13 069	16 406	7 244
	Four-quarters-ahead	7 140	10 088	18 606	23 787	7 950
	Average **b**	9 045	11 673	19 601	24 697	9 937
	Total sales over year ahead	18 992	25 705	45 620	57 697	21 992

Note: Results are for models estimated over the training period (March 2002 to December 2012). **a** Average RMSE across all three structural pine series. **b** Average forecast errors across all rolling forecasts estimated over the validation period.
Source: ABARES estimates

Table C3 Directional forecasting accuracy of various combinations of models (per cent)

Sales series	Time horizon	Model combination																	
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
Treated pine sales	One-quarter-ahead	83	83	83	83	83	83	83	33	75	75	33	75	50	75	75	50	33	75
	Two-quarters-ahead	82	82	82	82	82	82	82	82	82	82	82	82	73	82	82	73	64	82
	Three-quarters-ahead	50	60	60	60	60	60	60	60	60	60	60	60	60	60	60	60	60	60
	Four-quarters-ahead	67	67	67	67	67	67	67	44	67	67	44	67	56	67	67	56	44	78
	Average **b**	70	73	73	73	73	73	73	55	71	71	55	71	60	71	71	60	50	74
	Total sales over year ahead	100	100	100	100	100	100	100	78	100	100	78	100	100	100	100	100	78	100
Category 1 sales	One-quarter-ahead	100	100	100	58	92	100	100	100	100	100	100	100	100	100	100	75	100	100
	Two-quarters-ahead	100	100	100	91	91	100	100	100	100	100	100	100	100	100	100	91	100	100
	Three-quarters-ahead	100	100	100	70	80	90	100	100	100	100	100	100	100	100	100	70	90	90
	Four-quarters-ahead	89	89	89	44	89	89	100	100	100	89	89	89	89	89	89	56	89	89
	Average **b**	97	97	97	66	88	95	100	100	100	97	97	97	97	97	97	73	95	95
	Total sales over year ahead	67	67	67	44	78	67	67	67	67	67	67	67	67	67	67	56	67	67
Category 2 sales	One-quarter-ahead	50	42	92	67	75	92	83	83	83	75	50	50	42	92	33	92	92	92
	Two-quarters-ahead	27	73	82	73	55	91	82	82	82	73	27	27	73	82	27	73	91	91
	Three-quarters-ahead	50	60	80	70	60	90	70	70	70	70	50	50	60	80	50	80	90	90
	Four-quarters-ahead	67	33	56	44	56	56	44	44	44	44	56	67	33	56	56	44	56	56
	Average **b**	48	52	77	63	61	82	70	70	70	66	46	48	52	77	42	72	82	82
	Total sales over year ahead	44	56	33	44	33	56	33	33	33	67	44	44	56	33	56	56	56	56
Average **a**	One-quarter-ahead	78	75	92	69	83	92	89	72	86	83	61	75	64	89	69	72	75	89
	Two-quarters-ahead	70	85	88	82	76	91	88	88	88	85	70	70	82	88	70	79	85	91
	Three-quarters-ahead	67	73	80	67	67	80	77	77	77	77	70	70	73	80	70	70	80	80
	Four-quarters-ahead	74	63	70	52	70	70	70	63	70	67	63	74	59	70	70	52	63	74
	Average **b**	72	74	82	67	74	83	81	75	80	78	66	72	70	82	70	68	76	83
	Total sales over year ahead	70	74	67	63	70	74	67	59	67	78	63	70	74	67	74	70	67	74

Note: Results are for models estimated over the training period (March 2002 to December 2012). **a** Average directional accuracy across all three structural pine series. **b** Average directional accuracy across all rolling forecasts estimated over the validation period.
Source: ABARES estimates

Table C4 MAPE of various combinations of models (per cent)

Sales series	Time horizon	Model combination																	
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
Treated pine sales	One-quarter-ahead	4.5	4.5	4.5	4.5	4.5	4.5	4.5	17.0	7.1	7.3	17.0	7.1	8.9	7.3	7.3	8.9	15.9	7.2
	Two-quarters-ahead	5.0	5.0	5.0	5.0	5.0	5.0	5.0	25.8	8.7	7.7	25.8	8.7	12.7	9.0	7.7	12.7	21.7	9.3
	Three-quarters-ahead	5.4	5.4	5.4	5.4	5.4	5.4	5.4	28.7	8.4	6.5	28.7	8.4	11.2	6.2	6.5	11.2	19.6	6.7
	Four-quarters-ahead	5.8	5.8	5.8	5.8	5.8	5.8	5.8	34.3	9.9	6.6	34.3	9.9	13.3	5.4	6.6	13.3	26.6	6.3
	Average **b**	3.2	3.2	3.2	3.2	3.2	3.2	3.2	20.9	5.6	4.8	20.9	5.6	8.4	4.7	4.8	8.4	16.0	5.1
	Total sales over year ahead	3.2	3.2	3.2	3.2	3.2	3.2	3.2	22.5	5.6	4.1	22.5	5.6	8.4	3.4	4.1	8.4	17.1	4.0
Category 1 sales	One-quarter-ahead	3.5	3.5	3.5	9.9	3.8	3.6	3.0	3.0	3.0	2.7	3.5	3.5	3.5	3.5	3.5	6.5	3.6	3.6
	Two-quarters-ahead	4.5	4.5	4.5	14.8	4.3	4.8	4.6	4.6	4.6	3.4	4.5	4.5	4.5	4.5	4.5	9.6	4.8	4.8
	Three-quarters-ahead	4.6	4.6	4.6	14.9	3.5	5.0	6.2	6.2	6.2	3.2	4.6	4.6	4.6	4.6	4.6	10.2	5.0	5.0
	Four-quarters-ahead	4.2	4.2	4.2	18.6	3.6	4.4	7.9	7.9	7.9	3.4	4.2	4.2	4.2	4.2	4.2	12.3	4.4	4.4
	Average **b**	3.1	3.1	3.1	11.2	3.3	3.3	4.1	4.1	4.1	2.3	3.1	3.1	3.1	3.1	3.1	7.6	3.3	3.3
	Total sales over year ahead	2.8	2.8	2.8	11.7	3.5	3.1	4.5	4.5	4.5	2.5	2.8	2.8	2.8	2.8	2.8	8.1	3.1	3.1
Category 2 sales	One-quarter-ahead	35.4	87.2	9.6	10.3	10.6	9.3	8.0	8.0	8.0	56.6	35.4	35.4	55.8	9.6	25.2	8.6	9.3	9.3
	Two-quarters-ahead	68.9	121.1	12.1	11.0	12.1	12.4	9.1	9.1	9.1	49.9	68.9	68.9	66.9	12.1	36.8	9.6	12.4	12.4
	Three-quarters-ahead	95.3	129.7	13.3	16.8	11.9	14.6	9.3	9.3	9.3	43.3	95.3	95.3	81.4	13.3	48.4	11.8	14.6	14.6
	Four-quarters-ahead	115.8	187.9	14.0	22.9	10.0	15.7	9.3	9.3	9.3	37.7	115.8	115.8	120.4	14.0	57.6	16.1	15.7	15.7
	Average **b**	60.1	101.2	8.1	11.1	7.4	8.4	6.4	6.4	6.4	38.4	60.1	60.1	63.0	8.1	34.6	7.9	8.4	8.4
	Total sales over year ahead	67.5	107.1	8.1	11.4	6.6	8.3	4.9	4.9	4.9	43.5	67.5	67.5	65.8	8.1	37.2	7.7	8.3	8.3
Average **a**	One-quarter-ahead	14.5	31.7	5.9	8.2	6.3	5.8	5.2	9.3	6.0	22.2	18.6	15.4	22.8	6.8	12.0	8.0	9.6	6.7
	Two-quarters-ahead	26.1	43.5	7.2	10.3	7.1	7.4	6.2	13.2	7.5	20.3	33.0	27.4	28.0	8.5	16.3	10.6	12.9	8.8
	Three-quarters-ahead	35.1	46.5	7.8	12.4	6.9	8.3	7.0	14.7	8.0	17.7	42.9	36.1	32.4	8.0	19.8	11.1	13.1	8.8
	Four-quarters-ahead	41.9	65.9	8.0	15.8	6.4	8.6	7.6	17.2	9.0	15.9	51.4	43.3	45.9	7.8	22.8	13.9	15.6	8.8
	Average **b**	22.1	35.8	4.8	8.5	4.6	5.0	4.6	10.5	5.3	15.2	28.0	22.9	24.8	5.3	14.1	8.0	9.2	5.6
	Total sales over year ahead	24.5	37.7	4.7	8.7	4.4	4.8	4.2	10.6	5.0	16.7	30.9	25.3	25.7	4.7	14.7	8.1	9.5	5.1

Note: Results are for models estimated over the training period (March 2002 to December 2012). **a** Average MAPE across all three structural pine series. **b** Average forecast errors across all rolling forecasts estimated over the validation period.
Source: ABARES estimates

In terms of directional accuracy (Table C3), Combination_3 correctly predicted the direction of sales with greater success than Combination_5, Combination_7 and Combination_10 in almost all instances. The results in Table C3 also highlight Combination_6 as being one of the better combinations of models in terms of directional accuracy. However, the improvements in directional accuracy were relatively minor and Combination_3 generated more accurate point forecasts than Combination_6 in all cases but one.

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