MARSDEN JACOB ASSOCIATES

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Econometric Model Report

Biodiversity Offset Program

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A Marsden Jacob Report

Prepared for Biodiversity Conservation Trust
Marsden Jacob Associates Pty Ltd
ABN 66 663 324 657
ACN 072 233 204

e. economists@marsdenjacob.com.au
t. 03 8808 7400

Office locations
Melbourne
Perth
Sydney
Brisbane
Adelaide

Authors

Dr Jeremy Cheesman	Director
Prof Robert Breunig	Australian National University, Crawford School
Diksha Dahiya	Consultant

LinkedIn - Marsden Jacob Associates
www.marsdenjacob.com.au

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Acronyms

Refer to the Biodiversity Conservation Trust website for more detail on these terms https://www.bct.nsw.gov.au/, unless otherwise indicated.

ARIMA	Auto Regressive Integrated Moving Average
BAM	Biodiversity Assessment Method
BBAM	BioBanking Assessment Methodology
BCT	Biodiversity Conservation Trust
BCF	Biodiversity Conservation Fund
IBRA	Interim Biogeographic Regionalisation for Australia system
OTG	Offset trading group. Offset Trading Groups are groups of credit types that have similar characteristics.

1. Introduction

Marsden Jacob has been engaged by the Biodiversity Conservation Trust (BCT) to develop an econometric model to establish the charge for development proponents who choose to pay into the Biodiversity Conservation Fund (BCF). This report sets out the final recommended modelling approach.

1.1 Context

The NSW DPIE 2021 report Strengthening the Biodiversity Offsets Scheme A new approach to developer charges covers the background, context and rationale for implementing a new approach. Readers unfamiliar with the project context are encouraged to read this document. Key points are:

- In 2016 the NSW Government accepted the advice of Acil Allen Consultants to adopt an econometric methodology as the basis for the Calculator.
- The Calculator provides a dollar amount that a developer pays to the Fund for the BCT to take on the developer's offset obligation. The Calculator estimates what the BCT may need to pay in the future to offset this liability and includes a risk premium (for taking on the offset obligation) as well as an amount to cover the BCT's credit acquisition costs.

Strengthening the Biodiversity Offsets Scheme A new approach to developer charges identified several issues with the way that the Calculator is currently being used, along with proposed improvements. Some of these issues are identified in the commissioned review of the Calculator by EY Port Jackson Partners (PJP):

- The total Calculator charge is often being used as a credit price benchmark. The Calculator was not intended to be used this way. It includes the BCT's costs of delivery and a risk premium, which should not be a consideration in price.
- The number of transactions occurring in the open marketplace has, over time, become insufficient to support robust updates to the Calculator. As a result, calculated offset prices for some offset classes have been highly volatile.
- Observed market prices being used in the econometric model do not represent arms-length prices in some cases. Recorded prices for related-party transactions may not be representative of the cost of acquiring credits (to the BCT).

Strengthening the Biodiversity Offsets Scheme A new approach to developer charges notes the econometric model has been subject to independent expert reviews (in consultation with NSW Treasury) and found by these reviews to be a best-practice framework and econometric approach. Strengthening the Biodiversity Offsets Scheme A new approach to developer charges notes robust and reliable price estimates rely not only on having a methodologically sound model, but also on having sufficient information to feed into that model to produce high quality estimates.

Based on its observations and findings, PJP made six recommendations to the Department to improve the way developer charges are determined.

Box 1: PJP recommendation

In summary, PJP recommended that:

1. The BCT should be responsible for determining appropriate developer charges.

2. The BCT should be required to provide developers with a quote within 30 days, except in exceptional circumstances.

3. To determine charges, the BCT should issue quotes based on a method that considers and weighs three sources – (1) an econometric model, (2) a cost-structure model and (3) market soundings – according to the nature of the market for the credit class.

4. The method should calculate a developer charge **that reflects a reasonable estimate of the cost to the BCT of acquitting the obligation at the OTG level in a like-for-like manner with a modest margin to account for risk.**

5. The BCT should be allowed to take up to five years to acquit offset obligations.

6. The BCT should publish developer charges at the time of acquittal.

1.2 Project objectives

BCT engaged Marsden Jacob Associates as technical advisors to develop a new econometric model. The project objective for BCT **is to develop an econometric model for developer charges that reflects a reasonable forecasting estimate of the cost to the BCT of acquitting the obligation at the OTG level in a like-for-like manner with a modest margin to account for risk**. The scope of the econometric forecasting model covers the ecosystem credit market only at the offset trading group (OTG) level and for credits under the Biodiversity Assessment Method (BAM).

The econometric modelling approach will be one of three methods available to BCT to calculate developer charges (Box 1). In developing an econometric model BCT has asked that we:

- Identify which OTGs have enough trades to provide a robust price estimate using econometric methods.
- Assess whether a model capable of predicting prices of amalgamated OTGs or regional areas where sufficient trade data exists is appropriate.

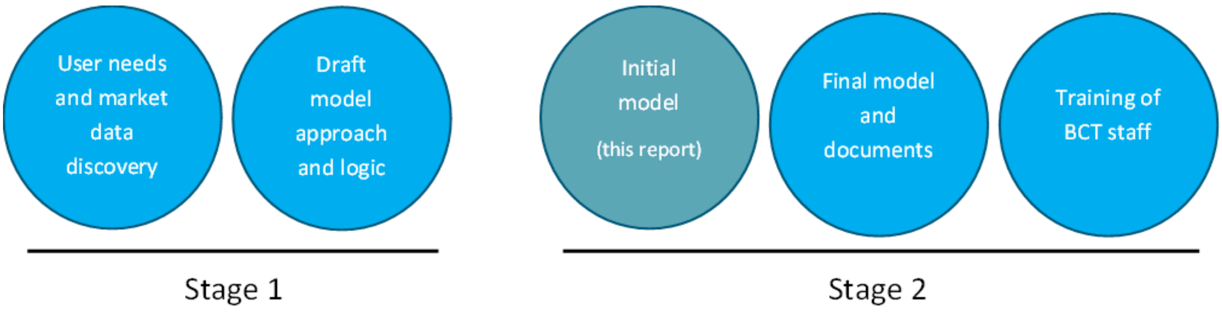
BCT has also asked that we:

- Recommend an approach for determining the risk margin to apply under the developer charge system from the econometric data.
- Prepare a report on the model methodology that succinctly explains the model approach, be suitably transparent and explainable to general scheme participants.
- Prepare a tool to develop a charge for the identified OTGs that can be implemented by BCT staff.

- Undertake training of relevant BCT staff; including the development of documentation to assist in implementing the developer charge tool.

Marsden Jacob's support to BCT covers two stages, with objectives and summaries set out below.

Figure 1: BCT econometric model review and development approach



Stage 1

In Stage 1, we assessed historical trade data and proposed and implemented previous modelling approaches to forecast offset prices. Based on the understanding developed from this work, we then assessed the high-level suitability of alternative forecasting approaches. Outcomes of this work are included in our Stage 1 report, provided separately to BCT. This work included:

- Cleaning, joining and cataloguing datasets provided by BCT to generate a robust set of offset trades. A data dictionary has also been prepared to facilitate modelling analysis.
- Developing an understanding of the historical context associated with the offset ecosystem trades. We engaged with accredited assessors and industry associations to understand drivers of observed trades and prices. This step is fundamental to developing a robust and defensible economic framework for ecosystem trades and the forecasting model, developing an appropriate economic framework underpinning the market, and calculating econometric model specifications.
- Reviewed previously recommended and implemented economic framework and econometric approaches to biodiversity offsets. The focus here has been on NSW offsets payment calculator, including (insert refs – ACIL ALLEN, Deloitte and BCT calculator). We have also reviewed submissions from the NSW Minerals Council into changes to the Biodiversity Conversation Regulation 2017 and supporting products.

Stage 2

In the second stage, we are developing the recommended model specification and testing its ability to robustly estimate and develop charges that **reflects a reasonable estimate of the cost to the BCT of acquitting the obligation** in a like-for-like manner and that BCT should be allowed to take up to three years to acquit offset obligations. We are also developing our approach to implementing a modest margin to account for risk. BCT has asked that we provide reasons for our Stage 2 advice based on research and evidence. We have worked with our colleague Professor Robert Breunig from the Crawford School at the Australian National University to develop the econometric model specification.

BCT has asked that our advice address matters including:

- The general model specification; including dependent and explanatory variables and functional form.
- How to ensure the model can appropriately account for changes in supply and demand for credits and thin markets.
- Any steps needed to ensure the model and parameters are statistically sound (e.g., parameters are stationary and structural breaks in time series are dealt with appropriately).
- How recommended changes should be made/implemented; including advising on the data sources and any adjustments that would be needed (e.g., adjustments to make data stationary).

This report is a Stage 2 deliverable. As shown in Figure 1, our next steps are developing formal model documentation that includes documentation for users on how to operate the forecasting model, the development of the forecasting model in Excel, and training of BCT model users.

2. Model specification and estimation technique

We have assessed the suitability of two types of econometric models for OTG markets: dynamic time-series models and a pooled cross-sectional model. The dynamic time series forecasting models in this Chapter are our preferred approach, based on our understanding of BCT objectives and modelling requirements.

Dynamic time series models allow us to capture the dynamic elements of pricing for forecasting OTG prices, whereas pooled cross-sectional models do not. Our evaluation shows that these dynamic elements are important to overall model performance.

This chapter outlines for the dynamic time series model:

- The general model specification: including dependent and explanatory variables and functional form.
- Steps we have taken to specify and test the recommended model (e.g., parameters are stationary and structural breaks in time series are dealt with appropriately).
- A discussion of how the model accounts for changes in supply and demand for credits and thin markets, and for risk.

Appendix 1 provides specification testing and results for the pooled cross-sectional model. We have provided these modelling results to allow readers to compare performance and outcomes for the alternative forecasting approaches.

2.2 Markets assessed

We evaluated forecasting suitability for multiple OTG markets using both modelling approaches: a dynamic time-series model and a pooled cross-sectional model. These market models followed two approaches, using data from 2010 to 2021:

- **OTG level models and forecasts:** modelling involved estimating econometric models using trade data from 2010 to 2021 at the Offset Trading Groups (OTGs) level. As noted in our Stage 1 report, at the OTG level there are six markets where there were sufficient trade data to develop robust forecasting models: Cumberland Plain Woodland OTG, River Flat Eucalyptus on Coastal Floodplains OTG, Shale Sandstone Transition Forests OTG, The Swamp Sclerophyl OTG and White Box OTG.
- These were OTGs where the initial sample sizes were greater than 30 observations—generally considered sufficient to estimate a simple regression model with a small number of covariates. As we describe below, further analysis led us to believe that we could only create compelling OTG-level forecast models for the two OTGs with the most data and largest coverage of years: Cumberland Plain

Woodland OTG and River Flat Eucalyptus on Coastal Floodplains OTG.

- **Regional level models:** we also evaluated the possibility of developing pooled OTG forecasting models where multiple OTGs were pooled at the IBRA Region level. There was insufficient data in almost every region to do this. Gaps in the time coverage made estimating a forecast model unviable. Where it was viable, the IBRA was dominated by a particular OTG and the resulting model was functionally equivalent to the OTG-level models that we present.

2.3 Dynamic Time Series Model

This section sets out the technical basis for the preferred time series model. This section assumes readers have some familiarity with ARIMA model specification and testing. An accessible introduction to ARIMA is provided here and here.

We use the annual evolution of average prices as part of estimating the preferred time series model. We use this approach on all markets pooled together and separately on the markets with the two largest number of transactions: Cumberland Plain Woodland OTG and River Flat Eucalyptus on Coastal Floodplains OTG. We also consider a residual, 'Other' group which accounts for all markets except Cumberland OTG and River Flat Eucalypt OTG.

2.3.1 The general model specification including dependent and explanatory variables and functional form

The general ARIMA model specifications [1] for the OTG price forecast model is:

$$\boldsymbol{Equation\ 1}: Y_t = \sum_{i=1}^{p} \emptyset_i Y_{t-i} + \beta X_t a_t - \sum_{j=1}^{q} \theta_j a_{t-j}\,, t = 1, \dots, T$$

Where *t* is the time series that denotes a year, *i* and *j* are the number of lags. *X* is a set of potential control variables which are described in Table 1 below.

Sample and variable selection

We began with 768 observations across 12 years. We dropped seven observations with a price equal to $1 which we believe are not "market transactions" in any meaningful sense. We began our investigation of the determinants of price using the widest possible set of variables. These are described in Table 1. We removed variables that were found to be statistically insignificant and when they did not impact on overall model performance, measured by comparing AIC and BIC of models.

Table 1: Description of the variables considered and data sources

Variable	Description	Reasoning	Data Source
$\boldsymbol{Y_t}$	Price paid per credit	Dependent variable	Biodiversity Conservation Trust
$\boldsymbol{Y_{t-i}}$	Lagged value of Y_t	Captures the general trend of price increases	Estimated from model
$\boldsymbol{a_t}$	Random errors	Captures anything that may affect Y_t other than Y_{t-i}	Estimated from model
$\boldsymbol{a_{t-j}}$	Lagged random errors	Captures the past random errors that may affect Y_t other than Y_{t-i}	Estimated from model
Number of credits	Average number of credits in the transactions at year *t*	This will capture \`quantity discount' effects – larger credit transactions may have a lower average price because of economies of scale and scope.	Biodiversity Conservation Trust
Non-Government	Fraction of the transactions at year *t* where the buyer was from the non-Government (1) sector	Government buyers pay less on average	Biodiversity Conservation Trust
Averaging	Fraction of the transactions in year *t* that involved averaging across multiple credit types.	Grouping different types of credits together may affect the average price	Biodiversity Conservation Trust
Tightness	Subjective assessment from 0-7 of market tightness (higher number indicates a tighter market)	Prices will be higher if the market is tighter	Biodiversity Conservation Trust
BAM	Fraction of the transactions in year *t* that were "BAM" transaction as opposed to a V-BAM transaction	A priori understanding that the BAM transactions are higher prices because of the way they are constructed	Biodiversity Conservation Trust

Estimation and Selection of ARIMA (p, d, q)

Our approach to model selection is based on the Box-Jenkins methodology which provides a useful framework to select the most efficient ARMA or ARIMA model.

We begin with a unit root test in Y_t, using a Dicky-Fuller test. The null hypothesis of a unit root was not rejected using the 1% level of significance. As a result we applied differencing in the series Y_t to make it stationary. Because the order of integration/differencing *d* for Y_t is not zero, our starting point is an ARIMAX (p, d, q) specification process.

We also estimate the autoregressive (AR) and moving-average (MA) parameters corresponding to models with different values of *p* and *q*. The optimal order of the AR and MA components is determined using coefficient hypothesis testing and Bayesian Information Criteria (BIC) minimization.

Given that we only have a short time series of 12 years, we approach the model selection by comparing a small set of feasible models with only one or two parameters in order to avoid poor forecasts due to estimation error.

We considered the following models for all markets and sub-markets (Appendix 2):

- ARIMA (1,0,1)
- ARIMA (0,1,0)
- ARIMA (0,1,1)
- ARIMA (1,1,0)
- ARIMA (1,1,1)

Based on our observations and estimation results (Appendix 2), our preferred optimal model is the simple exponential smoothing ARIMA (0,1,1) model, i.e., AR *(p)* and MA *(q)* components are of order 0 and 1 respectively with level of first-order differencing, *d* = 1.

Our simple exponential smoothing ARIMA (0,1,1) model uses an exponentially weighted moving average of the past values to filter out the noise and make better forecasts using the error correction form.

Our model choice is based on the following observations (results in Appendix 2):

- First order integrated/differenced models in Y_t , i.e., *d* = 1 fit better than those with no differencing.
- The autoregressive (AR) coefficient $\emptyset_i$ (Equation 1) for all first order integrated/differenced models is always statistically insignificant with no improvements in BIC. Therefore, we eliminate ARIMA (1,1,0) and ARIMA (1,1,1) models.
- Based on the BIC minimization, ARIMA (0,1,1) model proves to be a better fit than ARIMA (0,1,0) even when the moving-average (MA) coefficient (Equation 1) θ_j is statistically insignificant.
- The ARIMA (0,1,1) model passes the model stability test.
- The ARIMA (0,1,1) model provides reliable forecasts in a wide variety of business and economic time series modelling situations and is easy to update when additional years of data become available.

We drop two variables from our final, preferred model because they are statistically insignificant in every one of the ARIMA models that we estimated:

- “Number of credits”

- BAM

2.3.2 Diagnostic testing

We took a variety of steps to test the model and verify that it is statistically sound. Tests and other details can be found in Appendix 2. We checked that the parameters are stable and that there are no structural breaks. We verified that the stability conditions for our preferred ARIMA model are met. We checked the auto-correlation functions to check that we do not have unexplained variation in the model.

2.3.3 How the model accounts for changes in supply and demand for credits and thin markets.

BCT asked we explain how the preferred model accounts for changes in supply and demand for credits, and for thin markets. Our preferred model accounts for changes in supply and demand and thin markets in several ways.

Accounting for changes in supply and demand through past prices.

There is clear evidence that expectations about future credit availability and prices play an important part in observed offset prices. This occurs in at least two ways we discussed in our earlier report to BCT (1) proponents and credit sellers anchor price expectations using information about past credit trade prices (i.e., they demonstrate so-called adaptive expectations). (2) proponents and credit sellers develop credit price expectations based on current supply in the market and expectations of future supply and market tightness, and they update their understanding of the future over time (i.e., they demonstrate adaptive learning and bounded rationality in forming their expectations[1]).

Our model accounts for anchoring in past prices by incorporating the exponential smoothing ARIMA (0,1,1) model, i.e., AR *(p)* and MA *(q)* components are of order 0 and 1 respectively with level of first-order differencing, *d* = 1 for the lagged value of Y_t.

Accounting for changes in supply and demand through future price expectations.

As noted above, the second way supply and demand changes are accounted for in the market is through forward price expectations and understanding of forward market tightness.

Our model incorporates includes a tightness factor which addresses the future ease of buying credits in an OTG market. The market tightness variable is a constructed variable scaled from 1 (expectation is that in the next 18 months there will be no OTG market tightness) to 7 (expectation is that in the next 18 months the OTG market will be very tight). BCT will develop an assessment of market tightness, including through market sounding with brokers and potential credit suppliers. BCT will adjust future prices for OTG credits by changing their expectations around forward market tightness through the model directly. Historical market tightness as estimated through discussion with brokers familiar with OTG markets over 2010-21.

[1] See Evans, G. W., & Honkapohja, S. (2001). Learning and Expectations in Microeconomics. Princeton University Press

Thin markets

We have only estimated forecasts for markets where there are sufficient trades – i.e. markets that are not thin. As discussed in section 2.2, these were OTGs where the initial sample sizes were greater than 30 observations—generally considered sufficient to estimate a simple regression model with a small number of covariates.   As we describe above, further analysis led us to believe that we could only create compelling OTG-level forecast models for the two OTGs with the most data and largest coverage of years: Cumberland Plain Woodland OTG and River Flat Eucalyptus on Coastal Floodplains OTG.

In other markets where compelling OTG-level forecast models cannot yet be estimated we recommend using the other approaches PJP

2.4 Results

The parameter estimates of our exponential smoothing ARIMA (0,1,1) models for all markets pooled together and separately for Cumberland OTG, River Eucalypt OTG and "Other" OTGs are shown below.

Table 1: Description of the variables considered and data sources

D - $y_t, Price$

1Coefficient (Cumberland OTG) 2		Coefficient (River Eucalypt OTG) 3	Coefficient (All Markets) 4
		[redacted]	
[redacted]			
Number of Observations11	11	11	11
AIC201.73	153.14	198.67	201.31
BIC203.72	154.13	201.05	203.70

Note: ** indicate statistically significant at the 5% level. The brackets record 95% confidence intervals for variables.

Our main markets for analysis are Cumberland OTG (column 2) and River Eucalypt OTG (column 3). We have still included All markets (column 4) and "other" markets (column 5) in Table 3 for readers understanding.

We believe that the variables for Cumberland OTG and River Eucalypt OTG (non-government/government, Averaging, Tightness) will become significant overtime when more trade data becomes available.

The key interpretation and observations from the final model are discussed below.

Table 1: Description of the variables considered and data sources

Variable	Type	Reasoning	Interpretation
Differenced Price	Dependent variable	Variable that is affected by another independent variables	Average annual change in price paid per credit
Non-Government	Independent Dummy variable	Non-government buyers pay more for the credits than the government buyers on average. This is because government buyers have economies of scale.	It is estimated that non-government buyers pay XXX more than government buyers for every credit purchased in Cumberland OTG and River Eucalypt OTG respectively.
Averaging	Independent Dummy Variable	Credit prices are averaged across multiple credit types to difference between averaged and non-averaged trades. This can increase/decrease the price paid per credit.	It is estimated that when the trade involved averaging across credit types, average annual price paid per credit XXX for Cumberland OTG. Whereas it XXX for River Eucalypt OTG.
Tightness	Independent Variable	Subjective assessment from 0-7 of market tightness. Markets with 7 market tightness have higher prices per credit due to low supply whereas markets with 1 market tightness have lower prices per credit due to high supply.	It is estimated that average annual price paid per credit increases XXX with increase in market tightness for Cumberland OTG and River Eucalypt OTG respectively.
Constant	Intercept	Change in price paid per credit when all independent variables are equal to zero	It is estimated that the average annual change in the price paid per credit is XXX and $XXX with government buyer, no averaging and zero tightness for each Cumberland OTG and River OTG respectively.
ARMA (MA L1)	Lagged errors	Weight of the lagged error term	Negative weight (-.99) leads to downward trend in average annual price prediction in XXX OTG

Variable	Type	Reasoning	Interpretation
			whereas a positive weight (1.00) leads to upward trend in average annual price prediction in XXX OTG. This parameter enters the autocorrelation function of the dependent variable. For example the value of -XXX implies that the correlation between y and its lagged value equals XXX*(1 + XXX)^2) ≈ YYY

2.5 Forecasting

In this section, we show example forecasts for 5 years following 2021 to 2026 based on the ARIMA (0,1,1) model (Figure 2). It is important to emphasise that these forecasts are examples for illustration only, and should not be interpeted as BCT forecasts for the these OTG markets for the next years.

Actual forecasts will depend on several factors, including forward expectations around market tightness. In the current examples all values are estimated at historical means.

Figure 2: forecasts for all markets and separate markets (cumberland OTG, River eucalypt OTG and other OTGs)

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Appendix 1. Detailed model results

This Appendix includes the detailed model results and specification test results for all models. This technical information is included for transparency and completeness.

A1.1. Pooled cross-sectional model

This Appendix includes the model results and specification tests for the pooled cross-sectional model. Pooled cross-sectional forecasting models in this Appendix are not our preferred approach, based on our understanding of BCT objectives and modelling requirements, and assessed model performance.

Results are included for completeness and to allow comparison with our preferred dynamic model specification.

The model pooled model is defined as follows:

Equation 2: $y_{it} = \boldsymbol{x}'_{it}\boldsymbol{\beta} \quad + \tau_t + \tau_{Ot} + \varepsilon_{it}$

Where t denotes the time series, *i* is the OTGs in the model, the covariates x are listed and described in Table 1 and τ_t and τ_{Ot} are two-time trends as described below.

Variable	Description	Reasoning	Data Source
y_{it}, Price	Price paid per credit	Dependent variable	Biodiversity Conservation Trust
time trends	Increases by one for each year Separate trend for "other" offset trading group	Captures the general trend of price increases	Generated by research team
Indicators for offset trading group (OTG)	Five specific OTGs and one catch-all group: • Cumberland • River Eucalypt • Shale/Sandstone • Swamp/Sclerophyll • White Box • Other	Different price dynamics appear to be happening in different offset trading groups	Biodiversity Conservation Trust
numberof	Number of credits in the transaction	This will capture `quantity discount' effects	Biodiversity Conservation Trust
Non-Gov/ Government	Indicator for whether the buyer was from the Government (0) or non-Government (1) sector	Government buyers pay less on average	Biodiversity Conservation Trust
Buyer	Indictors for five main buyers: • OEH—Linking Landscapes through Local Action project • Roads and Maritime Services • Dept. of Infrastructure,	This will capture any buyer-specific effects	Biodiversity Conservation Trust

Variable	Description	Reasoning	Data Source
	Regional Development and Cities • Transport for NSW • Australian Rail Track Corporation		
Averaging	Indicator variable equal to one if trade involved averaging across multiple credit types	Grouping different types of credits together may affect the average price	Biodiversity Conservation Trust
DifferenceCT	The difference in days between the data that the credit was created and the date it was transacted	This variable attempt to control for market tightness—a shorter gap between credit creating and transaction could indicate a tighter market.	Biodiversity Conservation Trust
Tightness	Subjective assessment from 0-7 of market tightness (higher number indicates a tighter market)	Prices will be higher if the market is tighter	Biodiversity Conservation Trust
BAM	=1 if a "BAM" transaction as opposed to a V-BAM transaction	A priori belief that the BAM transactions result in higher prices	Biodiversity Conservation Trust
Indicator variables to control for outliers	We created three indicator variables to remove excessive influence of outlier observations detected in model specification tests i. The River-Flat OTG interacted with a time dummy for 2021 only ii. The Swamp Sclerophyl OTG interacted with a time dummy for pre-2019 observations iii. The Shale Sandstone OTG interacted with a time dummy for pre-2013 observations	Graphical analysis and statistical outlier testing revealed that these observations had an undue influence on the results and were not consistent with other observations in those three markets.	Generated by research team

In this model we examine the determinants of price for 693 transactions in the period 2010-2021. The main usefulness of this model is:

a. Identifying the correlations between observable characteristics and price
b. Identifying which correlations are significant even after controlling for other factors
c. A sense of the main variables which determine price in the 2010 - 2021 period.
d. While it can be used for forecasting, the time trend produces forecasts that have no dynamic aspect to them. It is probably preferable to use the time series models to predict prices unless:
    i. We have very good predictions (for the future) of the variables that determine price in this model are available; and
    ii. There is confidence that the model parameters are constant over time

Based on statistical hypothesis testing of the full unrestricted model; we made the following model simplifications:

- We combined the "White Box Offset Trading Group" with the "Other" group as it was always statistically insignificant in every model that we estimated.

  We combined these two offset trading groups below because the White Box Offset Trading Group only featured in 16 trades and was not distinguishable from other markets—not enough to undertake separate statistical analysis.

- We originally estimated a model with a separate "tightness" variable for each OTG. Using at F-test, we determined that the impact of tightness in each OTG was not statistically different than any of the other OTGs. We thus combined the separate tightness variables for each OTG into one tightness variable.

- We considered augmenting the model (Equation 1) with covariates Government/Non-government, Averaging and tightness only (Table 1). Using R-squared, we determined the model with Number of credits in transactions and BAM was not a good fit and the variables are never significant in any of our estimates. Therefore, we do not include them in our model which has little effect on the model results or the forecasts.

Results

In this section, we summarise the main conclusions from the model. Full model estimates are presented in the Appendix 2.1 below.

We only discuss the general direction of effects as this model is for the exploratory purpose for the readers. The effects discussed below are based upon the partial regression coefficients, so they reflect the impact of the variable after controlling for all variables from Table 3.

The signs of the coefficients match our expectations and are statistically significant at 5% level of significance unless otherwise indicated. Based on our estimation we observe the following:

- Prices trend up for all OTGs. For other OTG, the trend is slightly negative.

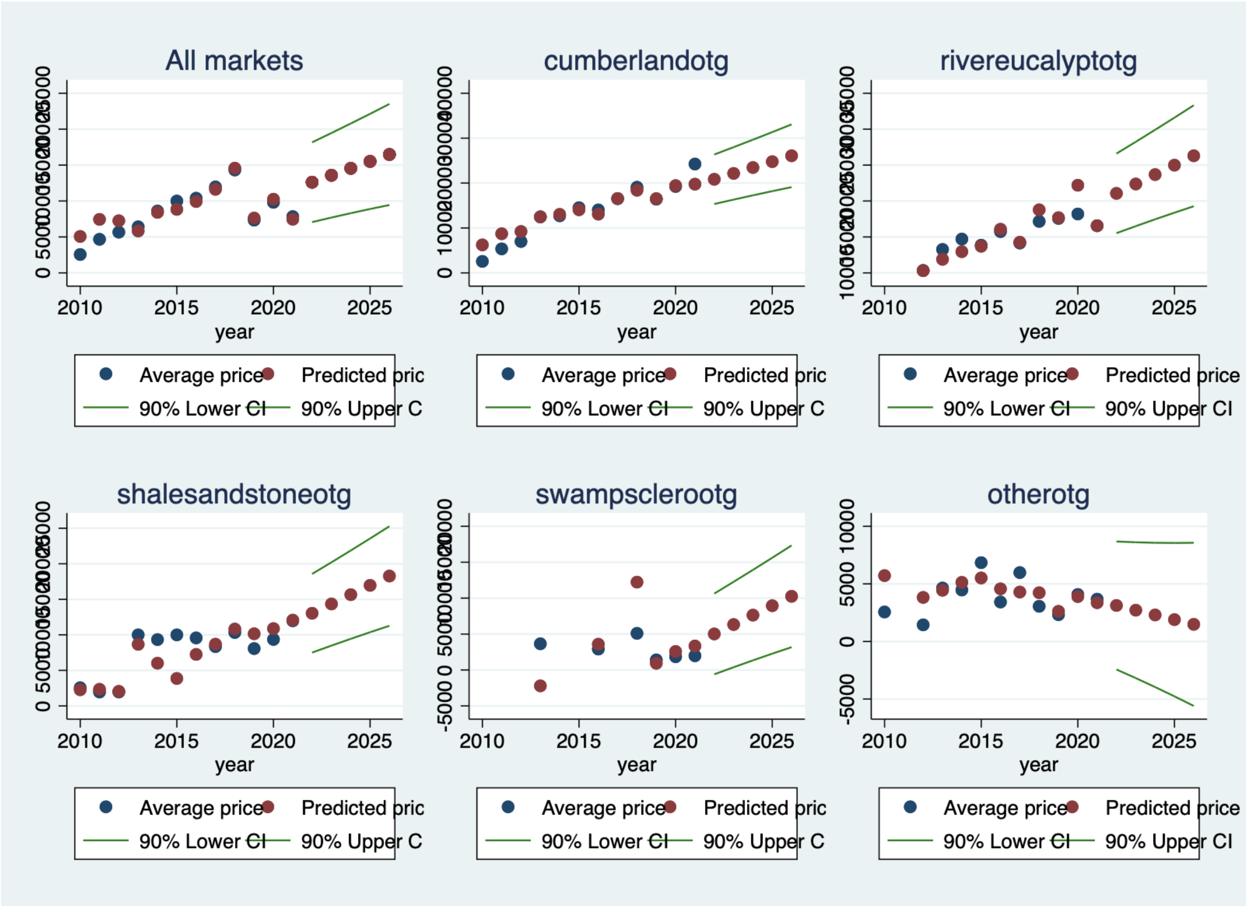
- Prices for all the specific OTGs for which we included indicator variables (see Table 3 above) are negative. The negative effects are largest for the Shale / Sandstone and Swamp / Sclerophyll OTGs.

- Prices are lower when the number of credits transacted is higher
- Prices are lower when the buyer is from the government
- Transport for NSW paid significantly higher prices than any other buyer; Australian Rail Track Corporation paid significantly lower prices than any other buyer.
- Transactions that involved averaging over different credit types had lower prices on average than those which did not
- The tightness variable constructed from the gap in days between a credit being created and being transacted was not statistically significant in the model.
- The subjective tightness variable was statistically significant with the expected direction—prices were higher when the market was tighter.
- BAM transactions had higher-prices on average than non-BAM transactions, even when controlling for all other factors

Forecasting

The in-sample forecast accuracy of the model is quite good for all markets and for the Cumberland and River Eucalypt OTGs. The model performs less well in matching the observable data for the other three OTG groups: Shale/Sandstone, Swamp / Sclerophyll and Other.

The downside of using this model for forecasting is that the only dynamic element in the model is the deterministic time trend. For this reason, we prefer to use time series models which allow us to capture the dynamic elements of pricing for forecasting. We now turn to a discussion of these.



All markets
cumberlandotg
rivereucalyptotg
shalesandstoneotg
swampsclerootg
otherotg
2010
2015
2020
2025
year
Average price
Predicted price
90% Lower CI
90% Upper CI

The STATA output below shows the full regression results for the pooled model across 12 years and 693 transactions.

```
      Source |       SS           df       MS      Number of obs   =       693
-------------+----------------------------------   F(20, 672)      =    123.53
       Model |  2.6765e+10        20  1.3383e+09   Prob > F        =    0.0000
    Residual |  7.2801e+09       672  10833434.1   R-squared       =    0.7862
-------------+----------------------------------   Adj R-squared   =    0.7798
       Total |  3.4046e+10       692  49198790.7   Root MSE        =    3291.4

-------------------------------------------------------------------------------------------------
                          price | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
--------------------------------+----------------------------------------------------------------
                          trend |   1309.347   87.85824    14.90   0.000     1136.837    1481.857
                                |
                  cumberlandotg |
                             1  |  XXX           YYY    -3.99   0.000
                                |
               rivereucalyptotg |
                             1  |  -XXX          YYY    -3.82   0.000                                    |
              shalesandstoneotg |
                             1  |   -12439.3    1215.77   -10.23   0.000    -14826.47   -10052.14
                                |
                  swampsclerootg |
                             1  |  -20457.52   1445.129   -14.16   0.000    -23295.04   -17620.01
                                |
                       otherotg |
                             1  |          0  (omitted)
                       numberof |   -2.63376    .780488    -3.37   0.001    -4.166249   -1.101272
            1.nongovernment1gov0 |   895.3512   425.6969     2.10   0.036     59.49505    1731.207
                                |
                        buyerno |
                             1  |
                             6  |
________________________________
                                |
                     1.averaging1 |                         -4.83   0.000
differencebwcreatedandtransacted |                         -0.94   0.346
         d2021#rivereucalyptotg |
                            1#1 |  XXX    YYY              -2.85   0.005
|
            dpre2019#swampsclerootg |
                            1#1 |   4843.794   1335.782     3.63   0.000     2220.986    7466.602
                                |
       dpre2013#shalesandstoneotg |
                            1#1 |   4087.275   1540.314     2.65   0.008     1062.867    7111.683
                                |
               otherotg#c.trend |
                             1  |  -1719.317   118.6257   -14.49   0.000    -1952.238   -1486.395
                                |
                      tightness |   XXX    YYY              5.07   0.000
                          1.BAM |                           2.56   0.011
                          _cons |                           9.72    0.000
```

The trend for the "other" OTG is found by combining the estimates of the two trend variables. It is negative and statistically significant.

```
 ( 1)  trend + 1.otherotg#c.trend = 0

------------------------------------------------------------------------------
       price | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
         (1) |  -409.9695    95.7428    -4.28   0.000    -597.9605   -221.9785
------------------------------------------------------------------------------
```

A1.2. Exponential smoothing models final results

This Appendix includes the model results and specification tests for the exponential smoothing model specifications

ARIMA(0,1,1) model for all markets.

```
ARIMA regression

Sample: 2011 thru 2021                          Number of obs     =         11
                                                Wald chi2(4)      =      68.76
Log likelihood = -93.33274                      Prob > chi2       =     0.0000

------------------------------------------------------------------------------------
                   |                 OPG
           D.price | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------------+----------------------------------------------------------------
price              |
nongovernment1gov0 |
               D1. |  -358.4208   3933.884    -0.09   0.927    -8068.692     7351.85
                   |
        averaging1 |
               D1. |  -6727.673   2246.295    -3.00   0.003    -11130.33   -2325.017
                   |
         tightness |
               D1. |    1001.37   504.6886     1.98   0.047     12.19839    1990.541
                   |
             _cons |   556.5466   600.0018     0.93   0.354    -619.4353    1732.529
-------------------+----------------------------------------------------------------
ARMA               |
                ma |
               L1. |   .1664939   .5797468     0.29   0.774     -.969789    1.302777
-------------------+----------------------------------------------------------------
            /sigma |   1169.792   506.0338     2.31   0.010     177.9843      2161.6
------------------------------------------------------------------------------------
Note: The test of the variance against zero is one sided, and the two-sided
      confidence interval is truncated at zero.


Akaike's information criterion and Bayesian information criterion

-----------------------------------------------------------------------------
       Model |          N   ll(null)  ll(model)      df         AIC        BIC
-------------+---------------------------------------------------------------
           . |         11          .  -93.33274       6    198.6655   201.0528
-----------------------------------------------------------------------------
```

ARIMA(0,1,1) model for Cumberland OTG

```
ARIMA regression

Sample: 2011 thru 2021                          Number of obs     =         11
                                                Wald chi2(4)      =      15.55
Log likelihood = -95.86481                      Prob > chi2       =     0.0037

------------------------------------------------------------------------------------
                   |                 OPG
           D.price | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------------+----------------------------------------------------------------
price              |
nongovernment1gov0 |
               D1. |   XXX         YYY         1.58   0.114
                   |
        averaging1 |
               D1. |                          -0.10   0.924
                   |
         tightness |
               D1. |                       1.20   0.228    -
                   |
             _cons |                       4.34   0.000
-------------------+----------------------------------------------------------------
ARMA               |
                ma |
               L1. |                                  0.324    -
-------------------+----------------------------------------------------------------
            /sigma |    1316.77          .        .       .            .           .
------------------------------------------------------------------------------------
Note: The test of the variance against zero is one sided, and the two-sided
      confidence interval is truncated at zero.

Akaike's information criterion and Bayesian information criterion

-----------------------------------------------------------------------------
       Model |          N   ll(null)  ll(model)      df         AIC        BIC
-------------+---------------------------------------------------------------
```

```
           . |         11          .  -95.86481       5   201.7296   203.7191
-----------------------------------------------------------------------------
```

ARIMA(0,1,1) model for River Eucalypt OTG

```
ARIMA regression

Sample: 2013 thru 2021                          Number of obs     =          9
                                                Wald chi2(4)      =     330.74
Log likelihood = -71.5719                       Prob > chi2       =     0.0000

------------------------------------------------------------------------------------
                  |                 OPG
          D.price | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
------------------+-----------------------------------------------------------------
price             |
nongovernment1gov0 |
              D1. |                          3.47   0.001
                  |
       averaging1 |
              D1. |                           0.89   0.371
                  |
        tightness |
              D1. |                          6.26   0.000
                  |
            _cons |                          1.64   0.101
------------------+-----------------------------------------------------------------
ARMA              |
               ma |
              L1. |                            1.29   0.196
------------------+-----------------------------------------------------------------
           /sigma |    605.214          .        .       .            .           .
------------------------------------------------------------------------------------
Note: The test of the variance against zero is one sided, and the two-sided
      confidence interval is truncated at zero.

Akaike's information criterion and Bayesian information criterion

-----------------------------------------------------------------------------
       Model |          N   ll(null)  ll(model)      df        AIC        BIC
-------------+---------------------------------------------------------------
           . |          9          .   -71.5719       5   153.1438   154.1299
-----------------------------------------------------------------------------
```

ARIMA(0,1,1) model for “Other” OTG

```
ARIMA regression

Sample: 2011 thru 2021                          Number of obs     =         11
                                                Wald chi2(4)      =       6.18
Log likelihood = -94.65704                      Prob > chi2       =     0.1860

------------------------------------------------------------------------------------
                   |                 OPG
           D.price | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------------+----------------------------------------------------------------
price              |
nongovernment1gov0 |
               D1. |   4824.197   2727.904     1.77   0.077    -522.3974    10170.79
                   |
        averaging1 |
               D1. |   196.8624   3210.739     0.06   0.951     -6096.07    6489.795
                   |
         tightness |
               D1. |  -608.9326   429.4557    -1.42   0.156     -1450.65    232.7851
                   |
             _cons |  -155.2161    297.562    -0.52   0.602     -738.427    427.9947
-------------------+----------------------------------------------------------------
ARMA               |
                ma |
               L1. |  -.9999915    16899.8    -0.00   1.000    -33123.99    33121.99
-------------------+----------------------------------------------------------------
            /sigma |   1180.011    9970650     0.00   0.500            0    1.95e+07
------------------------------------------------------------------------------------
Note: The test of the variance against zero is one sided, and the two-sided
      confidence interval is truncated at zero.

Akaike's information criterion and Bayesian information criterion

-----------------------------------------------------------------------------
       Model |          N   ll(null)  ll(model)      df         AIC        BIC
-------------+---------------------------------------------------------------
           . |         11          .  -94.65704       6    201.3141   203.7014
-----------------------------------------------------------------------------
```

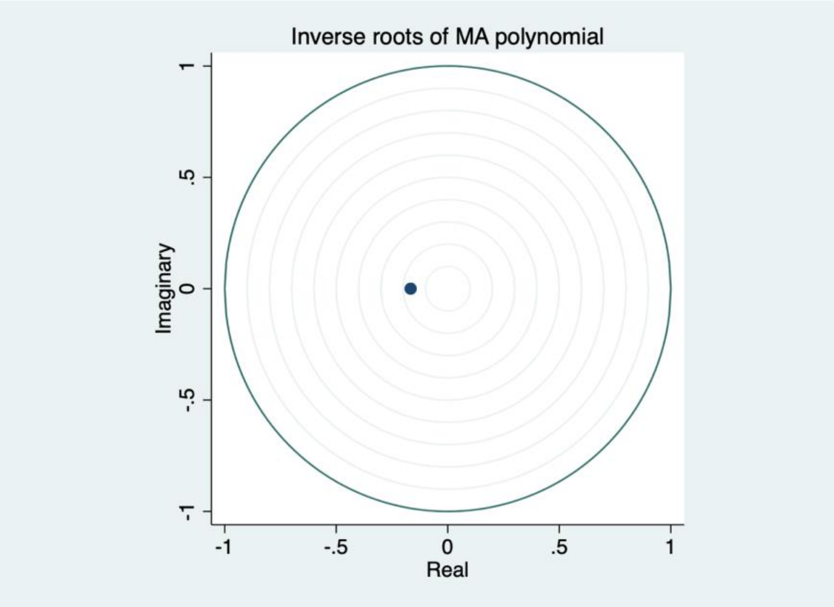
A1.3. Stability condition after estimating the parameters of an ARMA model

This Appendix provides results of the stability condition assessment for the dynamic time series ARMA model specification.

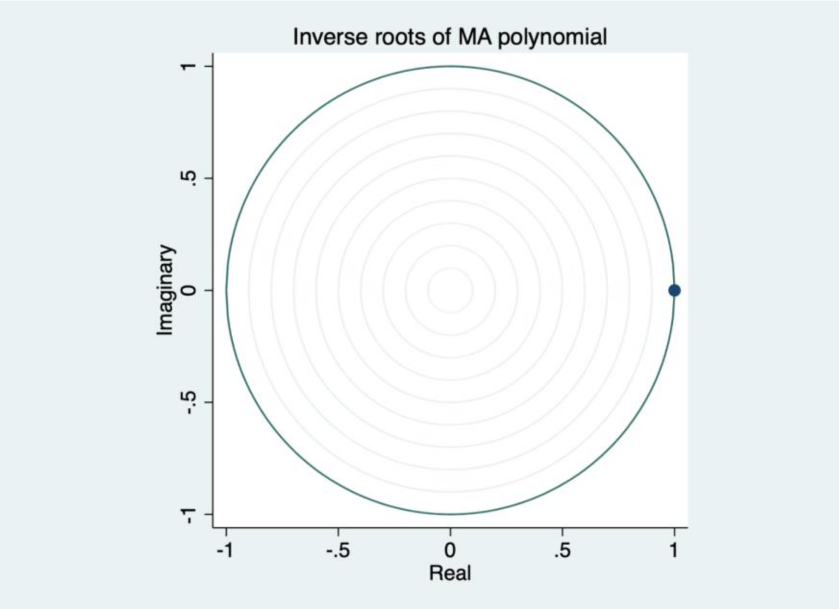
The diagram below shows that the inverse of the root of the AR polynomial lies inside the unit circle. Therefore, the process is stationary, invertible and has an infinite-order MA representation. Moreover, since the inverse of the MA root lies inside the unit circle, the estimated ARMA is invertible.

Note that the models for Cumberland and Other OTG lie near the border. However, in both cases the roots pass the test of being inside the unit circle. Additional years of data should improve this measure. The River Eucalypt OTG had too few observations to generate this diagnostic graph.

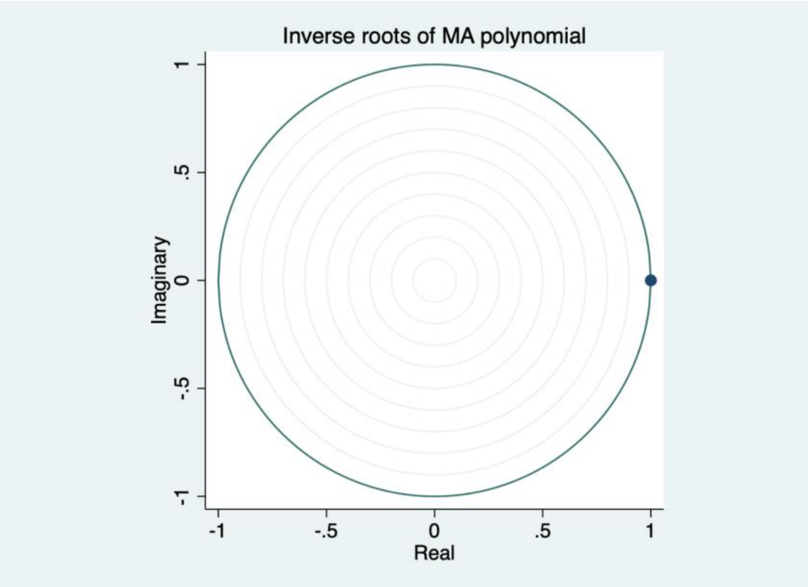
All markets



Cumberland OTG



Other OTG



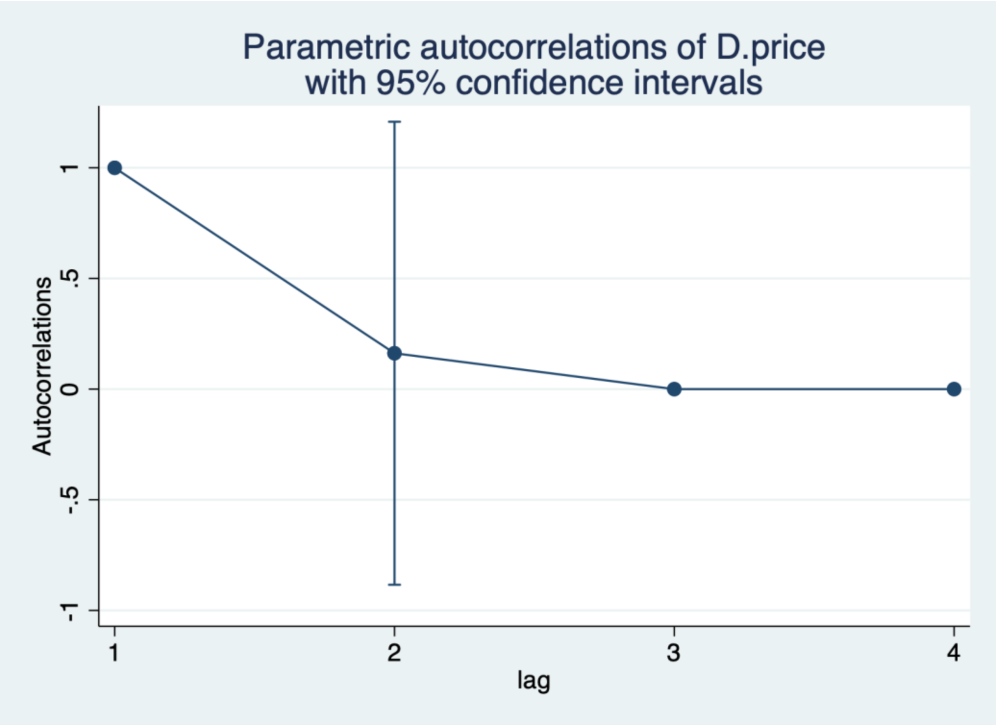
A1.4. Autocorrelation Function (ACF) plot on the residuals

This Appendix provides technical results assessing the autocorrelation function (ACF) for the ARIMA residuals. The ACF function provides information about the degree of autocorrelation in the residuals. In a well-specified model, the residuals should be white noise, i.e. they should follow a random-walk pattern.

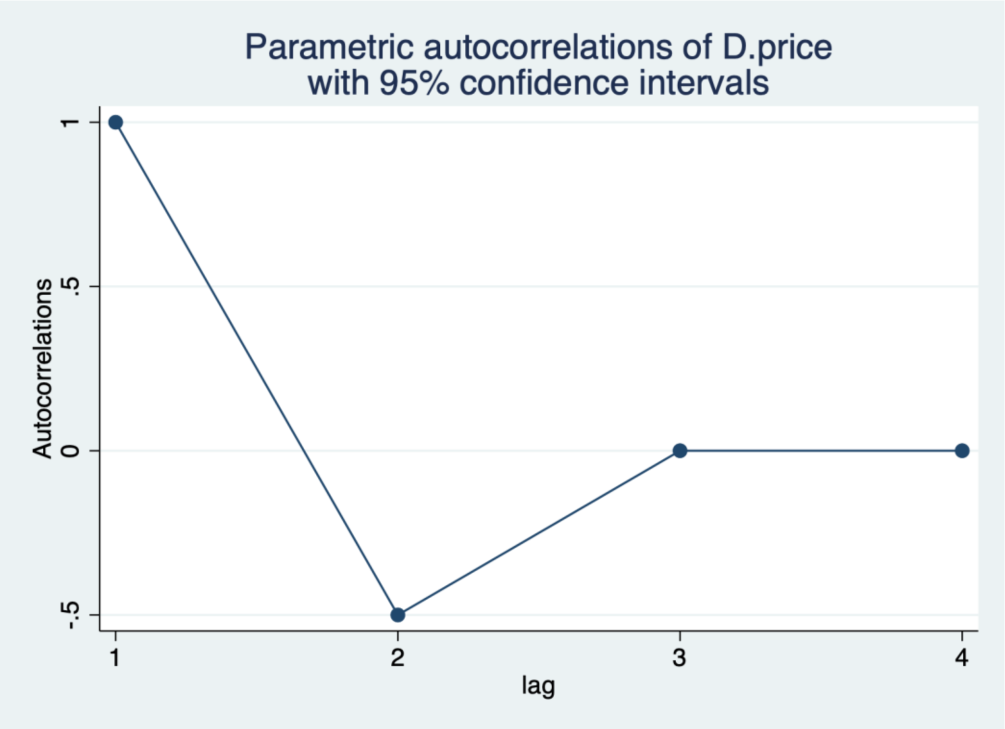
The time series is short in the OTG markets so the focus is on the residuals on the 2nd lag. If zero lies within the confidence bounds, then we accept that the model is well-specified by this measure.

The tests below show that the models for Cumberland and Other OTG do not pass the ACF diagnostic test. However, the estimated model still out-performs any of the other models we considered on the stability and model selection criteria. The River Eucalypt OTG had too few observations to generate this diagnostic graph. We expect the ACF may improve as additional years of data are added.

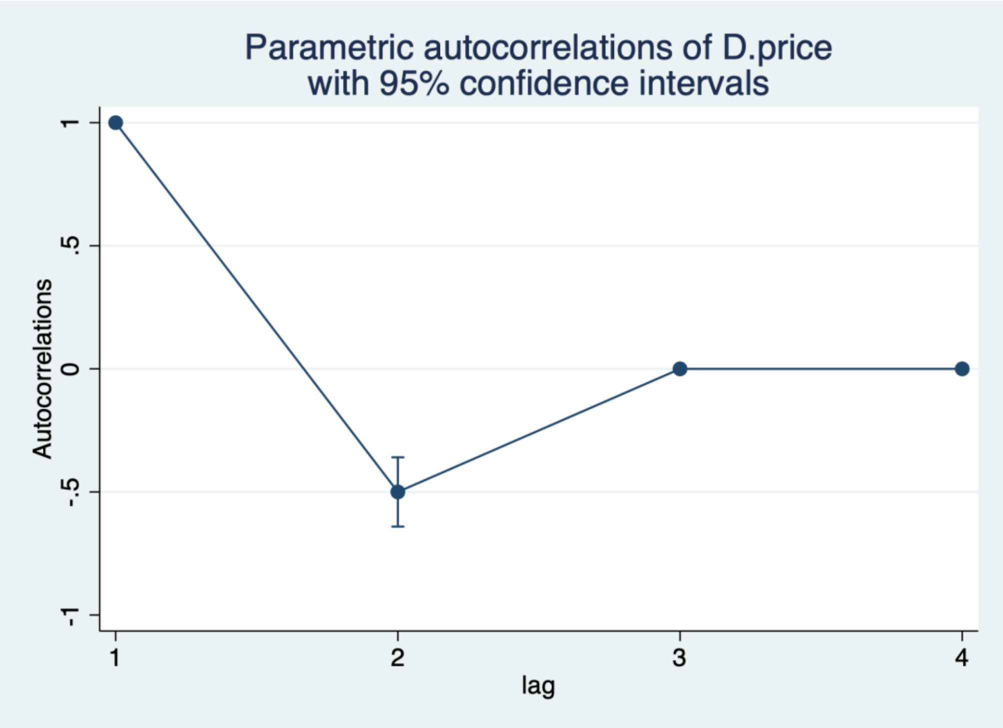
All markets



Cumberland OTG



Other OTG



Parametric autocorrelations of D.price
with 95% confidence intervals
Autocorrelations
1
.5
0
-.5
-1
1
2
3
4
lag

Appendix 2. Model data request

Ongoing model development will require a dataset compiled of the following:

Data field name	Description
Date of transaction	Date the transaction was conducted
Date BSA created	Date, the Biodiversity Stewardship Agreement, was created
Credit Type	Type of credit transacted, either BAM or BBAM.
Price	Price per credit in dollars
Steward agreement Number	A unique identifier associated with the Biodiversity Stewardship Agreement (BSA) or BioBanking Agreement
Number of credits	Number credit as part of the transaction
Plant Community Type	PCT involved in the transaction
Offset Trading Group	Defined Offset Trading Group
Seller	The type of the seller involved in the transaction
Buyer	The type of the buyer involved in the transaction
IBRA Sub-Region	The Interim Biogeographic Regionalisation for Australia

MARSDEN JACOB ASSOCIATES

Contact us

Dr Jeremy Cheesman
Director

jcheesman@marsdenjacob.com.au
0414 765 739

Marsden Jacob Associates Pty Ltd

03 8808 7400
economists@marsdenjacob.com.au
Marsden Jacob Associates
www.marsdenjacob.com.au