Carbon Leakage Review Consultation Paper 2 – Annex

Contents

1. Overview

This Annex presents and describes data and statistics underpinning the Review's analysis of carbon leakage. It describes the econometric methodology underlying the analysis of trade leakage and the approach taken to assess investment leakage at the firm level. In addition, the Annex sets out the key assumptions and limitations of the approaches taken.

2. Trade analysis methodologies and prior studies

The Review's sectoral analysis uses an econometric approach that draws on work by the Australian public service and academic research described here, and leverages the most detailed dataset available.

The methodology follows and builds on established research practices to model trade price elasticities using time series econometrics on import and export data. Extensions to existing methods include bounds testing. Other analytical strategies, such as using carbon prices as an input variable or emissions as a quantity to be modelled, were investigated but found not appropriate in the present context due to data limitations.

The Productivity Commission uses merchandise trade data collected by the Department of Foreign Affairs and Trade (DFAT) and the ABS Business Longitudinal Analysis Data Environment (BLADE) dataset to estimate the import demand elasticity of various import commodities.[1] Statistical models including error-correction models (ECM) and autoregressive distributed lag models (ARDL) are used to estimate long-run and short-run elasticity coefficients.

Branger et al. (2016) study the impact of carbon price on competitiveness-driven operational leakage at a geographically aggregated level (Europe and the rest of the world).[2] The effect of differences in carbon prices on net imports are estimated with Prais-Winsten and autoregressive integrated moving average (ARIMA) models. The estimated objective function is derived from an analytical trade model of Europe and the rest of the world with assumptions of perfect competition and no product differentiation. Demand and supply are determined by solving the profit constraint optimisation problem, which includes carbon costs in the budget constraint. There are many other examples of similar applications of statistical models in the academic literature.[3]

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[1] Bubonya, M., de Fontenay, C., Reysenbach, T., Smith, P. and Thiris, J. (2023), What Can We Learn About Industries' Vulnerability to Overseas Price Shocks from Merchandise Trade Data in BLADE?, *Conference Paper*, Productivity Commission.

[2] Branger, F., Quirion, P. and Chevallier, J. (2016), Carbon Leakage and Competitiveness of Cement and Steel Industries Under the EU ETS: Much Ado About Nothing, *The Energy Journal*, 37(3). http://dx.doi.org/10.5547/01956574.37.3.fbra

[3] A summary of relevant examples is provided in the UK Government 2014 ETS Review.

The Australian Treasury[4,5] and Reserve Bank[6] also estimate ECM models of varying specifications to measure the price sensitivity of Australian exports and imports. Their approach uses aggregate or macroeconomic trade and price indexes. In comparison, the method applied here uses micro (commodity) level data.

Elasticity estimates for categories of grouped goods that cover the 73 trade-exposed production variables (PV) under the Safeguard Mechanism Rule are discussed in Section 2.4 of the consultation paper.

Purpose and interpretation

Price elasticities for exports and imports of trade-exposed industries are used to assess leakage impacts for each commodity. Econometric modelling estimates the sensitivity of trade sectors to changes in prices between Australia and the rest of the world. This approach models price elasticities for exports and imports of trade exposed industries.

Elasticity estimates can be used to proxy how markets may respond to differences in price as a result of carbon costs and thereby provide an empirical estimate of carbon leakage risk through the trade channel.

These estimates should be interpreted as illustrations of relative magnitude rather than projections of the specific extent of leakage risk. Future responses in trade and production to changes in relative prices may differ from observed past responses. Further and importantly, the analysis is not a proxy for carbon leakage through the investment channel.

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[4] Beames, A. and Kouparitsas, M. (2015), Modelling Australia's Imports of Goods and Services, *Treasury Working Paper 2015-02*.

[5] Kouparitsas, M., Luo, L. and Smith, J. (2017), Modelling Australia's Exports of Non-Commodity Goods and Services, *Treasury Working Paper 2017-01*.

[6] Cole, D. and Nightingale, S. (2016), Sensitivity of Australian Trade to the Exchange Rate, *Bulletin*, Reserve Bank of Australia.

3. Assessing sectoral carbon leakage risk

The first step of the sectoral analysis is an assessment of carbon leakage risk. This is assessed using a traditional emissions-intensive trade exposure (EITE) approach but applied on a by-commodity basis to trade. Essentially, trade leakage is assessed for the Safeguard Mechanism's production variables, rather than for the facility, the firm, or the industry (although these are also meaningful units of analysis).

The second step assesses the impact of changes in price on trade volumes (tonnes). This provides information about the sensitivity of these trade flows to changes in (carbon-related) production costs and associated price changes. Note that these estimates are unique and specific to Australian trade flows for commodities covered by production variables, rather than being generally applicable. The sensitivity of trade volumes to changes in prices are combined with the estimated carbon cost changes in 2030 to estimate the plausible carbon leakage impact.

Estimated carbon cost as a share of product price

The 2030 carbon cost as a share of product price for each commodity is calculated by first estimating the carbon cost for each commodity. The carbon cost is estimated based on the emission reduction obligation under the Safeguard Mechanism taking TEBA baselines into account. In 2030, this is calculated as the difference between the 2022 emissions intensity baseline levels and the emissions intensities corresponding to the 2030 baseline levels. This rate is multiplied by the projected cost of Australian Carbon Credit Units (ACCUs) in 2030 (consistent with Australia's emissions projections).

ACCU prices are used as a proxy for the per tonne cost of abatement. In the case of onsite abatement, this reflects an economically rational assumption that onsite abatement is undertaken when abatement costs are equal to or cheaper than the cost of ACCUs. Assuming that the per tonne cost of abatement is equal to the projected ACCU price is appropriate because this is the best available proxy of the net present value of abatement investment. We expect that individual onsite abatement investments may have a lower or higher cost per tonne than the projected ACCU price in 2030. However, there may be other reasons why firms choose to undertake onsite abatement in preference to purchasing ACCUs.

Prices of commodities are drawn from multiple sources, and in most cases inferred from data on trade volumes and values between 2019 and 2023 inclusive. The unit prices of these commodities can vary significantly, accordingly results of computations are presented as ranges rather than point estimates. The projected carbon cost as a share of commodity prices, as outlined in section 2.3, is given as:

$$\frac{(Average\ Emissions\ Intensity_{2022} - Baseline\ Emissions\ Intensity_{2030}) \times ACCU\ price_{2030}}{Commodity\ Price\ per\ unit\ (e.g.\ tonne)} \times 100\%$$

The above calculates the by commodity carbon cost as share of final unit price. In this formula, the 'baseline emissions intensity in 2030' reflects the baselines of facilities that produce production variables corresponding to that commodity. For some production variables, the emissions intensity is also adjusted to reflect the emissions of intermediate inputs, such as for ammonia production used in urea production.

This in turn depends on an assessment of the TEBA status of each facility producing the production variable of interest, which would affect its baseline.

Some commodities are associated with multiple Safeguard Mechanism production variables, and facilities have more than one production variable, which may be associated with different commodities). To account for this, the following formula was used to estimate the projected carbon cost per unit of Safeguard production:

$$\frac{\sum_{\text{PVs for commodity},p} Q_p \cdot (EI_{\text{adjusted\_default, p}} \cdot \mathbf{eff}_p \cdot ACCU\ price_{2030})}{\sum_{\text{PVs for commodity},p} Q_p}$$

where:

- the sum is over each production variable p relevant to the good.

- Q_p is the total Safeguard production of the production variable p. The formula weights the emissions intensity for each production variable using the amount of production for that production variable.

- $EI_{\text{adjusted default},p}$ is the default emissions intensity for production variable p. Where the production variable has an emissions-intensive input that is a production variable corresponding to a different good, the default emissions intensity is adjusted by adding the emissions intensity of the input, which is scaled to reflect the amount of the input needed to produce the production variable.

- $\mathbf{eff}_p$ is a measure of the average difference between the baselines for a production variable in 2030 and the business as usual emissions for that production variable, as a percentage of the business as usual emissions (see below).

- $ACCU\ price_{2030}$ is the projected price of compliance units in 2030.

When there is just one production variable corresponding to a good, the formula simplifies to the previous one.

The difference in baselines for production variable p, $\mathbf{eff}_p$, representing the percentage of emissions for which compliance units would need to be surrendered and required to calculate the effective carbon cost, was estimated as follows:

$$\mathbf{eff}_p = \frac{\sum_{F(p)} BL_{F,p}^{\text{undeclined}} - BL_{F,p}^{2030}}{\sum_{F(p)} BL_{F,p}^{\text{undeclined}}}$$

where:

the sums take place over each facility $F(p)$ that have the production variable p.

$BL_{F,p}^{\text{undeclined}}$ is the '2022 undeclined baseline component' for facility F and production variable p, and represents the BAU emissions for facility F and production variable p.

$BL_{F,p}^{2030}$ is the estimated baseline component in 2030 for facility F and production variable p. If the facility is expected to get trade-exposed baseline-adjusted (TEBA) status, the facilities baseline in 2030 is assumed to reflect this.

Hypothetical Example: more than one production variable associated with a commodity

An example of a commodity where there is more than one production variable is polyethylene, for which there are two production variables: ethylene and polyethylene. Ethylene is an intermediate production in the polyethylene production process and most of the emissions associated with polyethylene are from ethylene production. Here is an example of how the estimated carbon cost as a share of product price would be calculated.

Suppose that there are 2 facilities, Facility A and Facility B, that produce both ethylene and polyethylene:

- Suppose that Facility A produces 100,000 tonnes of ethylene a year, which it uses to produce 100,000 tonnes of polyethylene a year.

- Suppose that Facility B produces 80,000 tonnes of ethylene a year, which it uses to produce 80,000 tonnes of polyethylene a year.

- Suppose that the BAU emissions of Facility A is 172,000 t CO_2-e, with 160,000 t CO_2-e from ethylene with 12,000 t CO_2-e from polyethylene.

- Suppose that the BAU emissions of Facility B is 171,200 t CO_2-e, with 160,000 t CO_2-e from ethylene with 11,200 t CO_2-e from polyethylene.

- Suppose that Facility A does not have TEBA status, so that its baseline in 2029-30 is 65.7% of its "undeclined baseline".

- Suppose that Facility B does have TEBA status, and its baseline in 2029-30 is 80% of its "undeclined baseline".

- The default emissions intensity of polyethylene production is 0.125 t CO_2-e per tonne of polyethylene, and the default emissions intensity of ethylene production is 1.79 t CO_2-e per tonne of ethylene.

For an existing facility F for which all production variables p are historical production variables, their baseline for years from 2029-30 onwards for a financial year is given by:

$$BL_F = ERC \cdot \sum_p EI_{\text{default},\, p} \cdot Q_p$$

where *ERC* is the 'emissions reduction contribution' that implements the baseline decline, which is 0.657 in 2029-30 for facilities that have not been given TEBA status (and a greater number for facilities that have); $EI_{\text{default},\, p}$ is the default emissions intensity for production variable p; and Q_p is the production of p in that financial year. The 'undeclined baseline component' for a facility F and production variable p in a financial year is accordingly given by $BL_{F,p}^{\text{undeclined}} = EI_{\text{default},\, p} \cdot Q_p$; and the baseline component in 2030 for facility F and production variable p is given by:

$$BL_{F,p}^{2030} = ERC \cdot BL_{F,p}^{\text{undeclined}} = ERC \cdot EI_{\text{default},\,p} \cdot Q_p.$$

We therefore have:

$$BL_{F_A,\,\text{polyethylene}}^{\text{undeclined}} = 0.125 \cdot 100{,}000 = 12{,}500$$

$$BL_{F_A,\,\text{ethylene}}^{\text{undeclined}} = 1.79 \cdot 100{,}000 = 179{,}000$$

$$BL_{F_B,\,\text{polyethylene}}^{\text{undeclined}} = 0.125 \cdot 80{,}000 = 10{,}000$$

$$BL_{F_B,\,\text{ethylene}}^{\text{undeclined}} = 1.79 \cdot 80{,}000 = 143{,}200$$

and:

$$BL_{F_A,\text{polyethylene}}^{2030} = 0.657 \cdot 12{,}500 = 8{,}213$$

$$BL_{F_A,\text{ethylene}}^{2030} = 0.657 \cdot 179{,}000 = 117{,}603$$

$$BL_{F_B,\text{polyethylene}}^{2030} = 0.8 \cdot 10{,}000 = 8{,}000$$

$$BL_{F_B,\text{ethylene}}^{2030} = 0.8 \cdot 143{,}200 = 114{,}560$$

We therefore have that the effectiveness parameter for polyethylene is:

$$\textbf{eff}_{\text{polyethylene}} = \frac{BL_{F_A,\,\text{polyethylene}}^{\text{undeclined}} + BL_{F_B,\,\text{polyethylene}}^{\text{undeclined}} - BL_{F_A,\text{polyethylene}}^{2030} - BL_{F_B,\text{polyethylene}}^{2030}}{BL_{F_A,\,\text{polyethylene}}^{\text{undeclined}} + BL_{F_B,\,\text{polyethylene}}^{\text{undeclined}}}$$

$$= \frac{12{,}500 + 10{,}000 - 8{,}213 - 8{,}000}{12{,}500 + 10{,}000} = 27.94\%$$

And the effectiveness parameter for ethylene is:

$$\textbf{eff}_{\text{ethylene}} = \frac{BL_{F_A,\,\text{ethylene}}^{\text{undeclined}} + BL_{F_B,\,\text{ethylene}}^{\text{undeclined}} - BL_{F_A,\text{ethylene}}^{2030} - BL_{F_B,\text{ethylene}}^{2030}}{BL_{F_A,\,\text{ethylene}}^{\text{undeclined}} + BL_{F_B,\,\text{ethylene}}^{\text{undeclined}}}$$

$$= \frac{179{,}000 + 143{,}200 - 117{,}603 - 114{,}560}{179{,}000 + 143{,}200} = 27.94\%$$

The projected carbon cost per unit of production would then be given by:

$$\frac{Q_{\text{polyethylene}} \cdot EI_{\text{polyethylene}} \cdot \textbf{eff}_{\text{polyethylene}} + Q_{\text{ethylene}} \cdot EI_{\text{ethylene}} \cdot \textbf{eff}_{\text{ethylene}}}{Q_{\text{polyethylene}} + Q_{\text{ethylene}}} \cdot ACCU\ price_{2030}$$

$$= \frac{180{,}000 \cdot 0.125 \cdot 27.94\% + 180{,}000 \cdot 1.79 \cdot 27.94\%}{180{,}000 + 180{,}000} \cdot \$67 = \$17.93$$

4. Trade model estimation

Econometric models are fitted on integrated merchandise trade data aggregated by production variable. ARDL model results are presented and used in leakage calculations since the ECMs can be reparameterised into an ARDL. Bounds testing is used to test for the presence of a long-run co-integrating relationship and separate models for imports and for exports are estimated. The models differ in the preferred explanatory and control variables. Export models use foreign trade-weighted GDP as a control while import models may use domestic GDP, final demand, or construction or agricultural indexes as appropriate.

A walkthrough of the ECM is used to motivate the relationship between ECM and ARDL, as well as the estimation of long run effects.

4.1   Restricted Error Correction Model (ECM)

Estimation of an ECM in this form can be broken down into two stages: (1) the estimation of the long run cointegrating relationship and (2) the estimation of the objective function. This is also known as a restricted ECM. The first long run relationship is given by:

$$\ln Q_{x,t} = \gamma_0 + \gamma_1 \ln P_{x,t} + \gamma_2 \ln D_t + v_t$$

Two-stage estimation requires all time series variables to be integrated of order 1 and the residuals of the first stage to be stationary if there is a long run cointegrating relationship. The lagged residuals from the first stage are used to estimate the ECM in the second stage if a long-run cointegrating relationship is identified:

$$\Delta \ln Q_t = \rho_0 + \rho_1 \Delta \ln P_{x,t} + \rho_2 \Delta \ln D_t + \alpha \hat{v}_{t-1} + \epsilon_t$$

The short-run and long-run elasticities are given by ρ_1 in the second stage and γ_1 in the first stage, respectively, while α captures the speed at which Q_t returns to equilibrium after some exogenous shock.

The full functional form of the ECM is:

$$\begin{aligned} \Delta \ln Q_{x,t} &= \beta_0 + \beta_1 \Delta \ln P_{x,t} + \beta_2 \Delta \ln D_t \\ &\quad + \alpha\big(\ln Q_{t-1} - \gamma_0 - \gamma_1 \ln P_{x,t-1} - \gamma_2 \ln D_{t-1}\big) + \epsilon_t \\ &= \beta_0 + \beta_1 \Delta \ln P_{x,t} + \beta_2 \Delta \ln D_t + \alpha \hat{v}_{t-1} + \epsilon_t \end{aligned}$$

- $Q_{x,t}$ is the quantity traded (either exported or imported) in tonnes at quarter t, where x is the commodity traded

- $P_{x,t}$ is the trade price (export or import price), taken as a proxy for the Australian output price

- D_t is the demand control variable

- α is the error correction coefficient

- γ_1 is the long-run price elasticity of demand

- γ_2 is the long-run effect of demand variable

- β_1 is the short-run price elasticity of demand

- β_2 is the short-run effect of demand variable

- ϵ_t is the error of the objective function

- v_t is the error of the long-run cointegrating relationship.

γ_1 is the coefficient of interest, quantifying the long run price elasticity. This is interpreted as a percentage change in $Q_{x,t}$ associated with a 1% change in price, all else equal (since all variables in the model are presented in natural logs).

The demand variable represents exogenous variation in Australian demand (for import models) and global demand (for exports models) that may jointly affect the price and quantity variable, consistent with previous modelling approaches.[7,8]

Australia is assumed to be a price taker in the global market for the commodities (i.e., takes rather than sets the world price). We therefore assume that export prices reflect the Australian cost of production and import prices reflect the foreign costs of production. Additionally, this also assumes Australian demand does not affect the global price. These simplifying assumptions are needed to make the estimations possible with the available data. For resource exports, Australia may possess some market power which impacts the results for these commodities. These assumptions and their limitations are discussed further in Section 1.7.

4.2 ARDL (Unrestricted ECM)

The restricted ECM can be expressed as a single equation unrestricted ECM:

$$\Delta \ln Q_t = \beta_0 + \beta_1 \ln(P_{t-1}) + \beta_2 \ln Q_{t-1} + \beta_3 \ln D_{t-1}$$
$$+ \sum_{i=0}^{p} \delta_i \, \Delta \ln(P_{t-i}) + \sum_{i=0}^{q} \theta_i \, \Delta \ln D_{t-i} + \sum_{i=0}^{r} \pi_i \, \Delta \ln Q_{t-i} + \epsilon_t$$

The unrestricted ECM can be further reparameterised as an ARDL. The ARDL is used to estimate the coefficients of interest across each commodity:[9]

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[7] Bubonya, M., de Fontenay, C., Reysenbach, T., Smith, P. and Thiris, J. (2023), What Can We Learn About Industries' Vulnerability to Overseas Price Shocks from Merchandise Trade Data in BLADE?, *Conference Paper*, Productivity Commission.

[8] Branger, F., Quirion, P. and Chevallier, J. (2016), Carbon Leakage and Competitiveness of Cement and Steel Industries Under the EU ETS: Much Ado About Nothing, *The Energy Journal*, 37(3). http://dx.doi.org/10.5547/01956574.37.3.fbra

[9] Software to estimate models provided by Natsiopoulos, Kleanthis, and Tzeremes, Nickolaos G. (2022), ARDL bounds test for cointegration: Replicating the Pesaran et al. (2001) results for the UK earnings equation using R,

$$\ln Q_t = \mu_0 + \sum_{i=0}^{p} \mu_{1,i} \ln(P_{t-i}) + \sum_{i=1}^{r} \mu_{2,i} \ln Q_{t-i} + \sum_{i=0}^{q} \mu_{3,i} \ln D_{t-i} + \epsilon_t$$

The re-expression of the ARDL as an ECM is described in Pesaran et al (2001), who also introduce the bounds test to test for the presence of a long-run cointegrating relationship using either a F or Wald test under a null of no cointegration and alternative hypothesis of cointegration.[10] The long run price elasticity coefficient is defined as $\frac{\sum_{i=0}^{p} \mu_{1,i}}{1-\sum_{i=1}^{r} \mu_{2,i}}$ in the ARDL model and $-\frac{\beta_1}{\beta_2}$ in the unrestricted ECM equation.[11,12] Lag length for model selection for a given commodity is determined by minimising the Akaike Information Criterion (AIC). The joint bounds test is used to test for a long-run cointegrating relationship between all dependent and independent variables.

Standard errors for the long run price elasticity, estimated using the delta method[13] with heteroskedastic and autocorrelation robust standard errors reported as well as the corresponding p-values.[14,15] Additional model specifications include trends and seasonally adjusted variables using the X-13ARIMA-SEATS algorithm are estimated.[16] Note that not all variables received a seasonal adjustment if no seasonal component was identified.

Natural logs are taken for all variables in every model. Each coefficient can be interpreted as an approximate percentage change after a 1% increase in the independent variable.

Journal of Applied Econometrics, 37(5), 1079-1090. https://doi.org/10.1002/jae.2919. A line by line derivation of the relationship between ECM and ARDL can be found at: https://blog.eviews.com/2017/04/autoregressive-distributed-lag-ardl.html#mjx-eqn-eq.ardl.1

[10] Pesaran, M. H., Shin, Y., and Smith, R. J. (2001), Bounds testing approaches to the analysis of level relationships, *Journal of applied econometrics*, 16(3):289–326.

[11] Natsiopoulos, Kleanthis, and Tzeremes, Nickolaos G. (2022), ARDL bounds test for cointegration: Replicating the Pesaran et al. (2001) results for the UK earnings equation using R, *Journal of Applied Econometrics*, 37(5), 1079-1090. https://doi.org/10.1002/jae.2919

[12] Pesaran MH, Shin Y (1999), An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis, *Econometric Society Monographs*. Cambridge University Press.

[13] Pesaran MH, Shin Y (1999), An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis, *Econometric Society Monographs*. Cambridge University Press.

[14] Newey, W. K., & West, K. D. (1987), A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica*, 55(3), 703–708. https://doi.org/10.2307/1913610

[15] Newey, W. K., & West, K. D. (1994), Automatic Lag Selection in Covariance Matrix Estimation, *The Review of Economic Studies*, 61(4), 631–653. https://doi.org/10.2307/2297912

[16] Sax, C., & Eddelbuettel, D. (2018), Seasonal adjustment by x-13arima-seats in r, *Journal of Statistical Software*, 87, 1-17.

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5. Merchandise trade data in BLADE

Data for key variables in model estimation is sourced from integrated merchandise trade and BLADE data. Raw trade data is presented as monthly observations at an ABN level. Each row contains the traded good's 10-digit Harmonised Tariff Item Statistical Code (HTISC), total value (customs value and free on board value), location of departure or arrival destination and weight of traded good. Key variables for modelling are:

- Customs value: Price paid to the supplier (transaction value). Used to record Australian import value in international trade statistics.

- Free on board (FOB): Transaction value including value of outside packaging and distribution services. Used to measure export value.

- Quantity traded: Quantity of goods imported or exported in tonnes (or converted to tonnes if a different unit is used).

The price of goods traded is derived by taking the total value of goods traded, divided by weight, which gives price per tonne of product.

5.1 Creation of export and import price variables

Prices are aggregated to a quarterly weighted average, where the weights are the quantity of goods imported or exported. This gives greater weight to transactions with higher quantities of a given commodity. Quantity weightings may reflect variation in prices due to long-term contract agreements and economies of scale. Furthermore, weightings reduce the influence of outliers in the reported price data, which are typically associated with low quantities of goods traded and which may be for a specific type of high value commodity.

Additionally, prices under long-term contracts and spot market prices may be different.[17] However, the data does not differentiate between how prices have been set. Exports transactions are converted to Australian dollars by the ABS. We assume that all exports transaction are invoiced in US dollars and convert the export prices at the relevant exchange rate. Specifically, monthly exchange rates were sourced from the BIS data portal and used to convert export prices to US dollars.

5.2 Demand variables

Domestic demand is proxied by different aggregate indexes across industries for import models depending on which provided the best model fit by minimising the AIC. For clinker and steel imports, the ABS' construction seasonally adjusted gross value added (GVA) index is used as a proxy for

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[17] Bubonya, M., de Fontenay, C., Reysenbach, T., Smith, P. and Thiris, J. (2023), What Can We Learn About Industries' Vulnerability to Overseas Price Shocks from Merchandise Trade Data in BLADE?, *Conference Paper*, Productivity Commission.

domestic demand. Ammonia and ammonium phosphate use a seasonally adjusted GVA based on agricultural growing seasons. The GVA index was sourced from ABS (September 2023). Australian Final Demand and Australian GDP are used as a proxy for domestic demand for all other commodities.

For export models, the commodity-invariant trade-weighted index of five top trading partners' GDPs are used as a foreign demand control. GDP data are seasonally adjusted and sourced from the OECD. The weights are based on DFAT export statistics for 2015 (China: 47.7%, Japan: 25.2%, the Republic of Korea: 11.5%, the United States: 9.0%, India: 6.6%). The weighting is the share of each destination country in the total value of Australia's exports for the commodity being modeled. Weights are calculated over the full time range of available trade data, which is 2003 Q3 to 2022 Q4.

5.3 Data quality

Across commodities, there were values in prices and quantities that appear to be outliers. However, given data in the DataLab is de-identified, it is often difficult to determine whether this is due to reporting error, or a correct but anomalous transaction.

A further set of models was run which remove the post-COVID and post-Ukraine invasion period. Using data for the period 2003 Q3 to 2019 Q4 deals with the global supply and demand shocks which may impact an estimate of the true underlying relationship. In some case, these models are preferred.

Additional models were run with the top 1% of prices removed from the raw dataset as a robustness check. Additional robustness checks were models with both the flat trade (import or export) price as well as a model which used a ratio of export prices to import prices (i.e. a proxy for relative prices) – which may be insightful for commodities such as petroleum, where long-term contracting matters for recorded prices at customs (in BLADE).

5.4 Sources of bias in the estimates and alternative approaches

For trade estimates, and in particular for exports models, the results from this analysis are likely to be biased towards zero, i.e. the 'true' elasticity is likely to be greater (higher negative numbers) than estimated. Unbiased estimates would likely show a greater response of quantities to price changes, and by extension higher trade leakage rates.

This is because this analysis has been unable to account fully for company level costs. This measure for landed import and export prices can therefore include both the supply side cost of production as well as the demand side impact on prices. This means that prices could rise due to domestic demand (causing imports to rise) and export prices could rise due to higher foreign demand – rather than due to changes in domestic or foreign production costs.

Trade-related variation in carbon policies may be better reflected by the changes in a firm's cost as opposed to changes in prices. This has implications for modelling options and whether a firm-based panel data approach could help to capture the variation. If changes in climate policies affect the cost base of firms, but overall costs are below the export price, then variation in export prices may not reflect potential changes in climate policies. We assess that import prices are more likely to be driven by global factors given that import prices are set by foreign produces. However, it was not practical to undertake a full firm-level micro-founded estimation given the time available and given the need to rely on the newly integrated National Greenhouse Gas and Energy Reporting (NGER) Scheme data into BLADE. We have relied on some descriptive firm-level sector data to inform the creation and checking of the ECM modelling.

In addition, the creation of aggregate commodity 'categories' assumes production variables groups to be homogenous products. This does not account for heterogeneity (differences) in production variables in the final estimates. This may create further (likely upwards) bias in the estimates. This risk cannot always be accounted for due to the production variable mapping and other data limitations.

6. Trade model regression results

The results of the ARDL (Unrestricted ECM) models are summarised in the following tables. The long run price coefficient is the primary estimate used in sectoral analysis and the key quantity in econometric modelling. Columns in the tables are defined below:

Commodity: Production variables estimated as a single commodity group.

Long run price: The estimated long run relationship between prices and trade quantities. Suppose the reported number is -1.5. For an import (export) model, the value indicates that a 1% increase in import (export) prices is associated with a 1.5% decrease in the import (export) quantity. Conversely, if the estimated value is positive 1.5, then a 1% change in prices would be associated with a 1.5% increase in the traded quantity. Standard errors are reported in parenthesis.

Long run price p value: Used to assess statistical significance of the long run price estimate against a threshold value (critical value). Smaller p values are typically attributed to 'greater' statistical significance. P values are closely related to the effect size and standard error. If a p value is small, then the standard error is small relative to the size of the estimated coefficient. This can be interpreted as a 'less noisy' or more 'precise' estimate, conditional on the model.

Adjusted R squared: An R squared estimate measures how much of the variation in import (export) quantity can be explained by the model. An Adjusted R squared makes a statistical adjustment for the number of variables used in the estimation procedure and is a more appropriate estimate of mode performance.

Bounds test p value: P value for the bounds test. If the p value is less than 0.05, then the Long Run Relationship (Bounds) is statistically significant and set to TRUE. A bounds test is used to assess whether a long relationship exists between import (export) quantity and the variables used in the model (prices and controls).

Seasonally adjusted: TRUE indicates when the X-13ARIMA-SEATS algorithm is applied to remove any seasonality in the data, if it exists.

Trend: TRUE indicates when a linear trend is added to the model to account for variation coming from some linear relationship between quantity traded and time.

Control variable: Type of variable used to statistically adjust for either domestic or international demand in the model.

The ARDL model generated more insightful results for imports than exports.

> For imports, there are 34 models we deemed useable, and 3 that generated an uninterpretable result (positive coefficient). In addition, 3 models failed due to lack of data in the time series or inability to be exported from BLADE use to identifiable issues; hydrogen, nickel ore and silicomanganese.

For exports, there were 24 deemed usable, 10 which were uninterpretable and 6 model fails (ammonium phosphate, clinker, flat glass, hydrogen, silicomanganese and titanium oxide).

Results

Table 1 and Table 2 display regression results for import models and export models respectively. Newey-West standard error is shown in parenthesis with long run price estimate is $\frac{\sum_{i=0}^{p} \mu_{1,i}}{1-\sum_{i=1}^{r} \mu_{2,i}}$ and standard errors are calculated by the delta method.

Some selected models were fit with data cut-off at 2019 as well as the full 2022 series. For some models, the post-COVID (cement) and post-Ukraine invasion (urea, refined petroleum) time series presented issues in estimation. In these situations, the model fit on 2003-2019 data is preferred.

Critical values for statistical significance

^: 0.10 *: 0.05 **: 0.01 ***: 0.001

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Table 1 - Import models summary

Commodity	Year	Trade price coefficient	Adjusted R squared	Bounds test p value	Time Trend	Control variable	Structural break date
Alumina	2022	-0.58** (0.2)	0.365	0.000	NO	Final Demand	
Aluminium	2022	-4.55** (1.46)	0.968	0.001	NO	Final Demand	
Ammonia	2022	-3.52** (1.21)	0.492	0.000	NO	Agriculture GVA index	
Ammonium Nitrate	2022	-0.97^ (0.54)	0.627	0.000	YES	Final Demand	
Ammonium Phosphate	2022	-0.3 (0.35)	0.443	0.050	YES	Agriculture GVA index	
Bauxite	2022	-2.84** (1.02)	0.470	0.005	YES	Final Demand	
Cement	2019	-2.46*** (0.34)	0.873	0.000	YES	Final Demand	
Clinker	2019	-0.82* (0.34)	0.921	0.000	YES	Construction GVA index	
Coal	2019	-1.14*** (0.29)	0.679	0.000	YES	Gross Domestic Product	
Crude Oil	2022	-0.59* (0.28)	0.907	0.330	YES	Final Demand	
Ethane and LPG	2022	-4.38*** (0.79)	0.962	0.279	YES	Final Demand	
Ethanol and Dried Distillers Grain	2022	-1.41** (0.44)	0.756	0.043	NO	Final Demand	
Ferro Manganese	2022	-0.18 (0.41)	0.565	0.001	YES	Gross Domestic Product	
Flat Glass	2019	-1.32*** (0.18)	0.618	0.000	NO	Final Demand	
Flat Steel Products	2019	-0.53* (0.2)	0.788	0.000	NO	Final Demand	
Glass Containers	2022	-8.5 (13.1)	0.916	0.206	NO	Final Demand	
Lime	2019	-3*** (0.16)	0.953	0.000	YES	Final Demand	
Lithium	2022	-0.55*** (0.05)	0.775	0.000	YES	Final Demand	
LNG	2022	-0.31* (0.13)	0.981	0.000	NO	Final Demand	
Long Steel Products	2022	-0.56^ (0.32)	0.467	0.000	YES	Construction GVA index	
Magnesia	2022	-2.17*** (0.55)	0.578	0.014	NO	Final Demand	
Manganese Ore	2022	-1.55*** (0.37)	0.617	0.000	YES	Final Demand	
Other Metal Ore	2019	-0.42* (0.17)	0.918	0.001	NO	Final Demand	
Other Refined Petroleum	2022	-0.31* (0.12)	0.994	0.006	YES	Final Demand	1/07/2009
Polyethylene	2022	-0.47* (0.22)	0.715	0.000	YES	Final Demand	1/01/2008
Crude Steel	2022	-3.89^ (2.15)	0.749	0.000	NO	Construction GVA index	
Pulp and Paper	2019	-0.77* (0.31)	0.877	0.001	NO	Final Demand	
Silicon	2022	-0.74*** (0.15)	0.911	0.034	YES	Final Demand	
Sodium Cyanide	2019	-5.15* (2.14)	0.727	0.001	YES	Gross Domestic Product	
Synthetic Rutile	2022	-0.2 (0.15)	0.746	0.000	YES	Final Demand	
Titanium Dioxide	2022	-1.24* (0.59)	0.820	0.017	NO	Final Demand	
Urea	2019	-1.71*** (0.23)	0.469	0.000	YES	Final Demand	

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Table 2 - Export modelling summary

Commodity	Year	Trade price coefficient	Adjusted R squared	Bounds test p value	Time Trend	Control variable	Structural break date
Alumina	2022	-0.27 (0.32)	0.842	0.012	NO	Trade weighted index	
Ammonia	2022	-3.42** (1)	0.745	0.209	NO	Trade weighted index	
Ammonium Nitrate	2019	-11.05 (10.57)	0.917	0.006	NO	Trade weighted index	
Bauxite	2019	-0.81** (0.26)	0.985	0.098	NO	Trade weighted index	1/10/2012
Cement	2019	-0.59 (0.5)	0.655	0.001	NO	Trade weighted index	
Ethane and LPG	2022	-0.84^ (0.47)	0.802	0.656	NO	Trade weighted index	
Ethanol and Dried Distillers Grain	2022	-0.64 (0.71)	0.989	0.127	NO	Trade weighted index	
Ferro Manganese	2019	-0.01 (0.11)	0.248	0.000	NO	Trade weighted index	
Flat Steel Products	2019	-0.41 (0.77)	0.619	0.010	NO	Trade weighted index	
Glass Containers	2019	-1.65* (0.8)	0.860	0.001	YES	Trade weighted index	
Lime	2022	-2.6** (0.8)	0.846	0.030	YES	Trade weighted index	
Lithium	2022	-1.19*** (0.22)	0.930	0.000	YES	Trade weighted index	
LNG	2022	-0.61*** (0.16)	0.992	0.000	NO	Trade weighted index	
Long Steel Products	2022	-0.45*** (0.08)	0.519	0.000	YES	Trade weighted index	
Other Refined Petroleum	2019	-1.03^ (0.57)	0.829	0.004	NO	Trade weighted index	
Polyethylene	2022	-1.41*** (0.15)	0.629	0.000	YES	Trade weighted index	
Crude Steel	2022	-3.6*** (0.82)	0.928	0.000	NO	Trade weighted index	
Pulp and Paper	2022	-1.52 (0.97)	0.934	0.000	NO	Trade weighted index	1/10/2009
Silicon	2022	-0.23 (0.4)	0.951	0.891	NO	Trade weighted index	
Synthetic Rutile	2022	-1.16** (0.41)	0.546	0.000	NO	Trade weighted index	1/01/2009
Treated Steel Flat Products	2019	-3.38*** (0.61)	0.647	0.067	NO	Trade weighted index	
Urea	2022	-1.09^ (0.61)	0.449	0.031	YES	Trade weighted index	

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7. Investment leakage risk indicator

Analysis of investment leakage is challenging. It requires commercially sensitive, extensive and accurate data, which is not generally available in the public domain. Further, it is not always feasible for CGE modelling to detect explicit impacts of policy on private investment. A simplified method to measure an industry's capacity to pass carbon costs through to consumers without loss of profit margin has been developed. The analysis relies on data collected through the NGER Scheme and BLADE datasets.

Using the NGER and BLADE economic activity datasets, we collect ABN based data (at the operating or controlling ABN level), the scope 1 emissions and profits. The analysis calculates the emissions to profits ratio, based on scope 1 emissions over 5 years of reported data (between 2017-18 to 2021-22 inclusive). Firm-level data is then classified by industry group to calculate an industry average. The top 5 and bottom 5 percentiles are removed as outliers.

This data is collected before the Safeguard reforms in 1 July 2023. As such, these firms are not necessarily the current or future Safeguard firm cohort. This analysis captures firms' (scope 1) emissions if they are above the 100,000 tonnes CO_2-e threshold. Results above the 95th percentile and below the 5th percentile are removed as they represent outliers. The absolute mean deviation is representative of deviations from the industry group average which illustrates the variability of individual firms within industries.

$$Ratio \ (emissions \ intensity) = \frac{Emissions_{firm,t}}{Profits_{firm,t}}$$

The absolute mean deviation is representative of deviations from the industry group average which illustrates the variability of individual firms within industries. There is some expectation of consistency of results between firms within the same industry group and the results are indicative of the high variability among firms in manufacturing industries. It is noted that these large firms represented by industry groupings have complex corporate structures and this analysis is reliant on information that the ABS derives from firm reported economic activity. Reporting for emissions differs on the basis of financial or profit reporting which adds additional uncertainty around the estimates.

There are several limitations to note. Firstly, the presentation of results is constrained by ABS output rules that prevent release of sensitive and identifying data. Industry groups were therefore created. Secondly, matching ABNs over time with de-identified data in BLADE poses risks that there are incorrect matches between firm emission data from the NGER scheme and ABS BLADE economic activity data. Thirdly, the measure of emissions and profits is on a firm-level basis rather than facility-level basis. It is unclear if the results are biased up or down.

Firm emissions below the Safeguard Mechanism coverage threshold are not included in the measure and there is potential for undercounting of emissions in firms' economic activity. Notably, there is little to no academic literature or government publications that have adequately researched and analysed the impact of policies on investment and the potential for leakage. A report published on

behalf of the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (2018) utilises a similar measure of emissions share of gross value added.

8. Treasury CGE modelling framework

8.1 Scenario overview

This section provides an overview of the key scenario assumptions for the options explored in the Review. The scenarios are stylised representations of what Australia and the world could look like if a particular course of action was taken to introduce the border carbon adjustment (BCA) into Australia. They are built by making evidence-based assumptions about future emission reduction actions. Scenarios do not represent an official economic forecast, but are instead model projections of emissions, energy use, and economic performance predicated on a specific set of assumptions.

The table below provides a comparable overview of key policy differences in each scenario. One set of scenarios applies a border carbon adjustment on cement, clinker and lime only, and a second set of scenarios applies the adjustment to the three sectors.

Table 3 - Key policy assumptions that define each scenario

	Scenario 1: BCA + No TEBA removal	Scenario 2: BCA + Import TEBA removal
Changes to aggregate emission task for Safeguard facilities	No change	No change
Policy	**Safeguard setting:** Existing Safeguard settings with a baseline decline rate of 4.9%. **TEBA:** Existing TEBA settings. **BCA:** Applied to the following import exposed sectors: Cement, clinker, and lime; Iron and steel; Ammonia and derivatives, including fertilisers.	**Safeguard setting:** Existing Safeguard settings with a baseline decline rate slightly lower than 4.9%. **TEBA:** TEBA concession for export exposed facilities only. **BCA:** Applied to the following import exposed sectors: Cement, clinker, and lime; Iron and steel; Ammonia and derivatives, including fertilisers.

The overall economic implications of a domestic border carbon adjustment or its effectiveness on carbon leakage and trade competitiveness will be sensitive to the technology assumptions and alternative climate policies included in the model. This analysis focuses on comparing alternative border carbon adjustment scenarios in a current policy setting. Other than adjusting Trade Exposed Baseline Adjusted (TEBA) settings, Safeguard Mechanism policy settings are assumed to stay constant across all three scenarios.

8.2 Modelling framework

The analysis of the domestic and international trade effects of a potential Australian border carbon adjustment combines three strands of models that capture the salient aspects of facility level abatement decisions, domestic market interactions and global market constraints. While each strand of analysis is represented by three different workhorse models, collectively they provide a comprehensive unified assessment of how potential policy changes that influence facility level

production decisions will impact the Australia domestic economy, trading partners and specific industries.

Figure 1 illustrates the flow of information into each model used for this assessment, starting with the Model of Industrial and Resource Abatement (MIRA).

Figure 1 – Unified modelling framework for assessing a potential Australian BCA
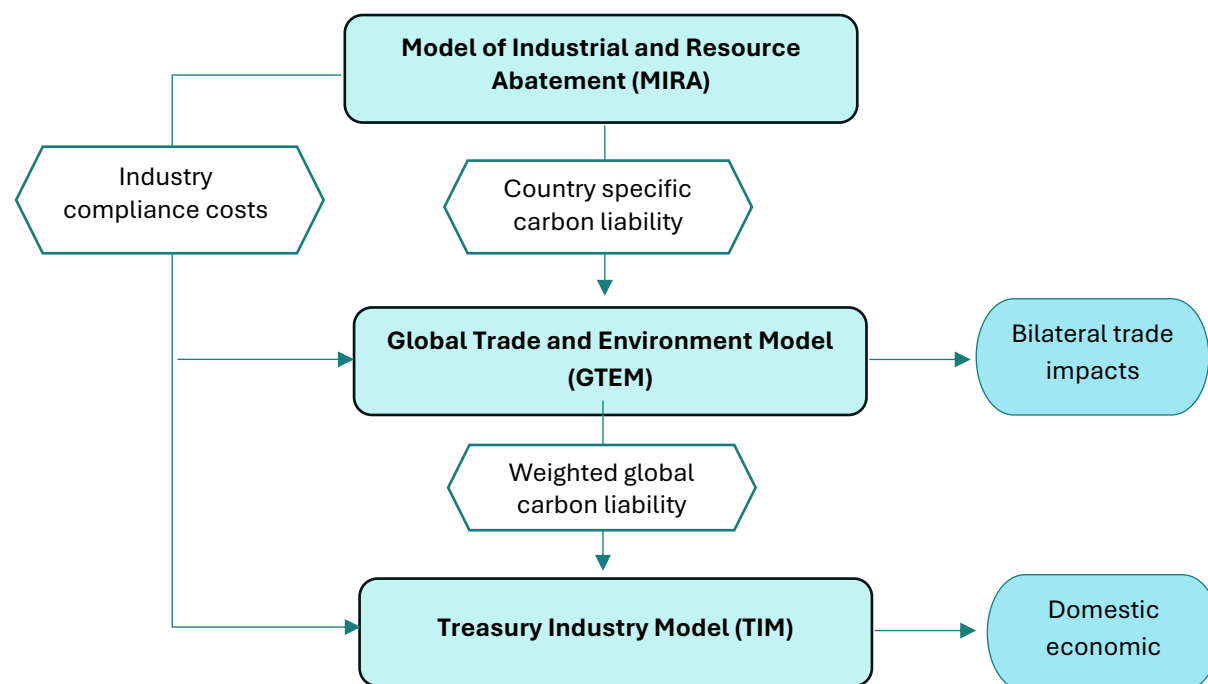
The three models, as described further below, were used to calculate the BCA liability.

8.3   Model of Industrial and Resources Abatement

Treasury's MIRA model is a partial equilibrium techno-economic model of least cost abatement for large industrial emitters that are part of the Safeguard Mechanism. It provides bottom-up detail on how these facilities may decarbonise through both investment in onsite decarbonisation technologies and purchasing of offsets.

MIRA models the behaviour of large industrial facilities by selecting the least cost set of technologies and carbon credit units to achieve abatement required under emission constraints such as the Safeguard Mechanism. Production volume assumptions are aligned with facility emission projections drawn from.

Detailed information on economic and technical parameters of abatement technologies comes from a range of sources, including propriety data by Reputex, external reports and analysis and information from agencies. Abatement technology assumptions have been further refined and adjusted based on advice from a technical advisory group consisting of representatives from Commonwealth agencies.

Key outputs include take-up of technology by individual facilities over time, costs over business-as-usual investment, offset take-up, and the associated level of emissions reduction. Outputs and

technology input data from MIRA have been used to calibrate the Treasury Industry Model. This includes costs for emissions response functions and the share of technology and offsets that large emitters use to meet their emissions reduction obligations.

8.4 Global Trade and Environment Model

The Global Trade and Environment Model (GTEM) is a dynamic global computable general equilibrium model with the capability to address total, sectoral, spatial and temporal efficiency of resource allocation. It captures the impact of policy changes on large numbers of economic variables in all sectors of the economy, including gross domestic product, prices, consumption, production, trade, investment, efficiency, competitiveness and greenhouse gases.

GTEM models each region as a stylised economy consisting of households, government and producers (industries or sectors). Household and governments consume a fixed proportion of national income, with the remainder allocated to national savings. Households and governments allocate their consumption expenditure to individual commodities according to an optimisation framework (to maximise their utility). Producers source inputs to minimise the production cost of their output. The savings from each region are pooled globally to fund investment across regions based on relative rates of return. Domestic and international trade enables all markets to clear. All prices are expressed relative to the global nominal exchange rate (which is the model numeraire).

GTEM provides global and regional projections of emissions and economic activities across a wide range of potential scenarios and outlooks. This includes shifts in technology costs, production and consumption patterns, economic structures, trade in goods and services, international investment flows and trade in emissions units.

GTEM is a recursive dynamic CGE model. This means that the behaviours of agents within the model are based on past and current outcomes, rather than forward looking expectations. Recursive dynamic models sequentially solve a series of yearly static economic models under conditions of certainty in competitive markets.

GTEM used for this modelling aggregates the world countries into 11 regions representing individual countries or groups of countries, including the United States, China, the European Union, India, Malaysia, Indonesia, Vietnam and the Republic of Korea. Each region in the model is linked through the bilateral trade of goods and services and investment flows over time as well as emissions permit trade if applicable.

8.5 The Treasury Industry Model

The Treasury Industry Model (TIM) is a forward-looking, multi-sector dynamic general equilibrium model of the Australian macroeconomy. As a general equilibrium model, TIM captures the economy's interconnectedness, showing the net effects of policy or other exogenous changes to the economy across firms, government, a representative household, and the rest of the world.

TIM is well-suited to informing advice on the transmission of events from one sector to related sectors and the broader economy. This can include scenarios such as the introduction of innovative technologies, changes in demand for goods by consumers, changes in foreign markets for exports or

changes in the costs of imports used in production. Given this, TIM is particularly well-suited to understanding the economy's response to persistent shocks, including anticipated changes to policy (such as a long-term transition to net zero).

Agents in the model, being households, government, firms, and the rest of the world, respond rationally to policy and technological change, providing a whole-of-economy view on key economic measures. This change occurs endogenously over time in response to changes in TIM's assumed (exogenous) economic parameters. Additionally, the high degree of industry and commodity disaggregation in TIM allows for a comprehensive understanding of how changes in technology, consumer preferences and other changes in demand, such as demand for exports, lead to changes in production processes across sectors.