Carbon Leakage Review Final Report – Annex

Contents

1 Overview

This Annex provides further technical detail on the analytical approaches and results underpinning the Review's analysis of carbon leakage. This includes 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 and provides an overview of updates since the analysis was published in Consultation Paper 2.

2 Trade analysis methods and prior studies

The Review's sectoral analysis used an econometric approach that drew on work by the Australian public service and academic research described here and leveraged the most detailed dataset available.

The methodology followed and built 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 to be 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) were used to estimate long-run and short-run elasticity coefficients.

Branger et al. (2016) studied the impact of carbon prices 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 were estimated with Prais-Winsten and autoregressive integrated moving average (ARIMA) models. The estimated objective function was 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 were 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]

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

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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), available here.

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

[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.

Elasticity estimates for categories of grouped goods that cover the 75 trade-exposed production variables (PV) under the Safeguard Mechanism Rule are discussed in Section 2.4 of the Final Report.

Purpose and interpretation

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

Updates to analysis for the Final Report

The following updates and improvements were made to the analysis for the Final Report:

- Aligning with changes in the Safeguard Mechanism prescribed PVs (*National Greenhouse and Energy Reporting (Safeguard Mechanism) Rule 2015* (31 August 2024)).
- Updated production data for each PV from Emissions Intensity Determinations were used where available. Production data was used to calculate trade leakage risk for each PV.
- Updated baseline emissions calculations used to calculate the difference in baselines for production variable *p*, $\mathbf{eff}_p$. This was used to estimate the projected carbon cost per unit of Safeguard production (see section 3).
- Updated price data for nickel, crude steel, crude oil and lithium ore.
- Inclusion of new entrants based on estimated production data and best practice emission intensities.
- Where trade data for the year 2022 appeared to be an outlier due to COVID-19, Ukraine war impacts, or other market volatility, it was replaced with a more appropriate value (such as an average from 2019 to 2023).

3 Assessing sectoral carbon leakage risk

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

The second step assessed the impact of changes in price on trade volumes. This provided 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 were 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 was calculated by first estimating the carbon cost for each commodity. The carbon cost was estimated based on the emission reduction obligation under the Safeguard Mechanism, taking TEBA baselines into account. In 2030, this was calculated as the difference between the 2022 emissions intensity baseline levels and the emissions intensities corresponding to the 2030 baseline levels. Note that the analysis does not include emissions from onsite electricity generation. Onsite electricity generation has a separate emissions intensity in the Safeguard Mechanism Rule. The emissions reduction rate was multiplied by the projected cost of Australian Carbon Credit Units (ACCUs) in 2030 (consistent with Australia's emissions projections 2023).

ACCU prices were used as a proxy for the per tonne cost of abatement. In the case of onsite abatement, this reflected 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 were 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 of the Final Report, 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.

This in turn depended on an assessment of the TEBA status of each facility producing the production variable of interest, which would affect its baseline. The carbon cost for goods that have multiple production variables are weighted by production. Where goods have material inputs that are also covered by production variables (such as alumina for aluminium), these were adjusted to include the carbon cost of the input material, based on an input multiplier that is the ratio of input materials to final goods per tonne.

Some commodities are associated with multiple Safeguard Mechanism production variables, and some 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:

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

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.
- $EI_{\text{default},p}$ is the default emissions intensity for production variable p.
- $\mathbf{eff}_{\mathbf{p}}$ 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*, $\mathbf{eff}_{\text{p}}$, 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 was assumed to reflect this.

To calculate $\mathbf{eff_p}$ the facility level baselines were apportioned for each PV weighted by production. Baseline components were then aggregated across multiple facilities to calculate $\mathbf{eff_p}$ for each PV.

The analysis considers the change in emissions associated with the Safeguard Mechanism decline rates (including any anticipated TEBA arrangements) between 2024 and 2030. Investment in onsite abatement or new emissions reduction technologies that result in decreases or step-changes in emissions intensity were reflected in revised 2030 baseline projections.

To account for the differences in projected emissions and the 2030 baseline projections, the data was 'normalised' to reflect industry changes (e.g. production or emissions intensity) that may occur in line with the baseline projections. The method for normalisation was updated for the Final Report, and facility-level calculated normalisation factors applied to each facility's 2022 business-as-usual emissions and 2030 decline rate adjusted emissions.

Other changes to estimated carbon costs as a share of unit prices were largely attributable to updated data sources including from 2024 Emissions Intensity Determinations, as well as updates to baseline projections.

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 $\mathbf{eff_p}$ parameter for polyethylene is:

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

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

And the $\mathbf{eff_p}$ parameter for ethylene is:

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

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

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

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

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

4 Trade model estimation

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

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

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:

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

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:

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

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:

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

- $Q_{x,t}$ 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
- ν_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 export 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.

ARDL (Unrestricted ECM)

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

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

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

[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), available here.
[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, *Journal of Applied Econometrics*, 37(5), 1079-1090, available here. A line by line derivation of the relationship between ECM and ARDL is available here.

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

The re-expression of the ARDL as an ECM was described in Pesaran et al (2001), who also introduced 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 was 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 was determined by minimising the Akaike Information Criterion. The joint bounds test was 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, were reported as well as the corresponding p-values.[14,15] Additional model specifications including trends and seasonally adjusted variables using the X-13ARIMA-SEATS algorithm were estimated.[16] Note that not all variables received a seasonal adjustment if no seasonal component was identified.

Natural logs were 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.

[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, available here.

[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, available here.

[15] Newey, W. K., & West, K. D. (1994), Automatic Lag Selection in Covariance Matrix Estimation, *The Review of Economic Studies*, 61(4), 631–653, available here.

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

5 Merchandise trade data in BLADE

Data for key variables in model estimation were 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 was derived by taking the total value of goods traded, divided by weight, which gives price per tonne of product.

Creation of export and import price variables

Prices were 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. Export transactions were converted to Australian dollars by the ABS. We assumed that all export transactions were invoiced in US dollars and converted to 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.

Demand variables

Domestic demand was 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,

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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.

the ABS construction seasonally adjusted gross value added (GVA) index was used as a proxy for domestic demand. Ammonia and ammonium phosphate used a seasonally adjusted GVA based on agricultural growing seasons. The GVA index was sourced from ABS (September 2023). Australian Final Demand and Australian GDP were 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 were used as a foreign demand control. GDP data were seasonally adjusted and sourced from the OECD. The weights were 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 was the share of each destination country in the total value of Australia's exports for the commodity being modeled. Weights were calculated over the full time range of available trade data, which is Q3 2003 to Q4 2022.

Data quality

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

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

Sources of bias in the estimates and alternative approaches

For trade estimates, and in particular for export 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 assessed that import prices are more likely to be driven by global factors given that import prices are set by foreign producers. 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 National Greenhouse Gas and Energy Reporting (NGER) Scheme data newly integrated 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 variable 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 was 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 (or export) model, the value indicates that a 1% increase in import (or export) prices is associated with a 1.5% decrease in the import (or 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 (or 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 (or 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 due 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. The 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 were 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 was preferred.

Table 1 - Import models summary[18]

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	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	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	

[18] **Critical values for statistical significance**: ^0.10 *: 0.05 **: 0.01 ***: 0.001

Table 2 - Export modelling summary[19]

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	

[19] **Critical values for statistical significance**: ^0.10 *: 0.05 **: 0.01 ***: 0.001

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 collected ABN based data (at the operating or controlling ABN level), the scope 1 emissions and profits. The analysis calculated 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 was then classified by industry group to calculate an industry average. The top 5 and bottom 5 percentiles were removed as outliers.

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

This data was 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 captured firms' (scope 1) emissions if they were above the 100,000 tonnes CO_2-e threshold. Results above the 95th percentile and below the 5th percentile were removed as they represented outliers. 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 based on 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 were not included in the measure and there is potential for undercounting of emissions in firms' economic activity. Notably, there was 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) utilised a similar measure of emissions share of gross value added.

8 Treasury CGE modelling framework

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 focused 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 were assumed to stay constant across all three scenarios.

Modelling framework

The analysis of the domestic and international trade effects of a potential Australian border carbon adjustment combined 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).

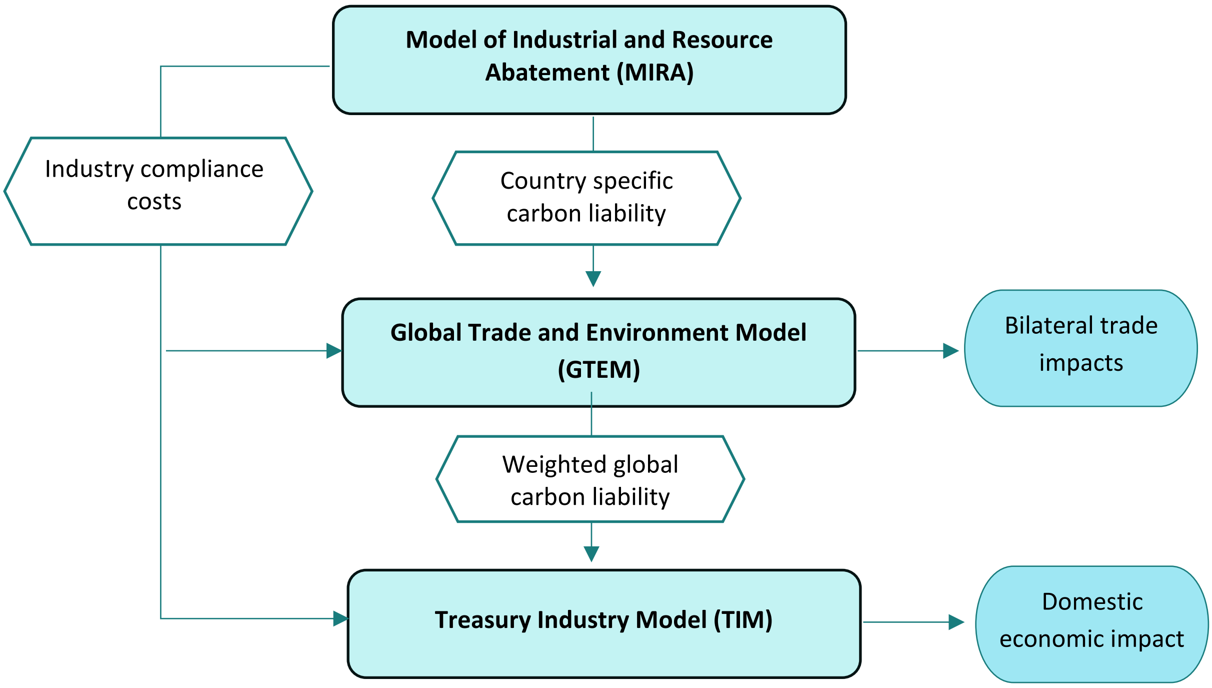

Figure 1 – Unified modelling framework for assessing a potential Australian BCA

The three models, Model of Industrial and Resource Abatement (MIRA), Global Trade and Environment Model (GTEM) and Treasury Industry Model (TIM), were used to calculate the BCA liability. These models are described further below.

Model of Industrial and Resources Abatement (MIRA)

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.

Global Trade and Environment Model (GTEM)

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.

The Treasury Industry Model (TIM)

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.

9 Supplementary Tables

Table 4 - Commodity categories and Safeguard Mechanism Production Variables

Commodity categories	Safeguard Mechanism Rule, Schedule 2, Table 1, Item number[20]	Safeguard Mechanism Rule, Schedule 2, Table 2, Item number[21]	Safeguard production variables[22]
Alumina	4		Alumina
Aluminium	3		Aluminium
Ammonia	5		Ammonia
Ammonium nitrate	6		Ammonium nitrate
Ammonium phosphate	8; 9		Diammonium phosphate; Monoammonium phosphate
Basic non-ferrous metal	28 - 30; 32		Lead bullion; Refined lead; Zinc in fume; Copper anode
Bauxite		4	Bauxite
Cement	25		Cement produced from clinker and supplementary cementitious material
Clinker	24		Clinker not used by facility to make cement
Coal	13	1	Coke oven coke; Run-of-mine coal
Crude oil		7 - 10	Extracted oil and gas; Stabilised crude oil or condensate (stabilisation only); Stabilised crude oil (integrated extraction and stabilisation)
Ethane and LPG		14; 15	Ethane; Liquified petroleum gas
Ethanol and dried distillers grain	46 - 51		Wheat protein products (dried gluten); Dried wheat starch; Wheat based dried distillers grain; Ethanol - 95; Ethanol - absolute; Beverage grade ethanol
Ferro-manganese	34		Ferromanganese alloy
Flat glass	1		Bulk flat glass
Flat steel products	19		Hot-rolled flat products produced at primary steel manufacturing facilities
Glass containers	2		Glass containers
Iron ore		2	Iron ore
Lime	26		Lime
Lithium ore		5	Lithium ore
LNG		10 - 13	Processed natural gas (processing only); Processed natural gas (integrated extraction and processing); Liquefied natural gas (from unprocessed natural gas); Liquefied natural gas (from processed natural gas)

[20] Trade-exposed production variables that are also manufacturing production variables.
[21] Trade-exposed production variables that are not manufacturing production variables.
[22] Per current *National Greenhouse and Energy Reporting (Safeguard Mechanism) Rule 2015*.

Commodity categories	Safeguard Mechanism Rule, Schedule 2, Table 1, Item number[20]	Safeguard Mechanism Rule, Schedule 2, Table 2, Item number[21]	Safeguard production variables[22]
Long steel products	18; 21		Hot-rolled long products produced at primary steel manufacturing facilities; Hot-rolled long products (cold ferrous feed)
Magnesia	31		Caustic calcined magnesia
Manganese ore	33	3	Manganese sinter; Manganese ore
Nickel products	36 - 38		Primary nickel products from nickel bearing inputs; Primary nickel products from imported intermediate nickel products; Intermediate nickel products from nickel bearing inputs
Other metal ore		6	Run-of-mine metal ore
Refined petroleum	53		Petroleum refinery feedstocks
Polyethylene	44; 45		Ethene (ethylene); Polyethylene
Primary steel[23]	17		Primary steel
Pulp and paper	39 - 43		Tissue paper; Packaging and industrial paper; Printing and writing paper; Newsprint; Pulp
Silicomanganese	35		Silicomanganese alloy
Silicon	27		Silicon
Sodium cyanide	10		Sodium cyanide
Synthetic rutile	11		Synthetic rutile
Titanium dioxide	12		White titanium dioxide pigment
Treated steel flat products	23		Treated steel flat products
Urea	7		Carbamide (urea)
Emerging industry: lithium hydroxide	54		Lithium hydroxide
Emerging industry: phosphoric acid	59		Phosphoric acid
Emerging industry: Rare earth oxides	60		Rare earth processing
Emerging industry: Renewable diesel	58		Renewable diesel
Emerging industry: Renewable aviation kerosene	57		Renewable aviation kerosene

[23] Not including steel made from cold ferrous feed/scrap.

Table 5 - Additional trade data

Commodity	2023 Import value ($m AUD)	2023 Export value ($m AUD)	Total trade ($m AUD)	Manufacture or Resource industry
Crude steel	49	59	108	Mfg
Long steel products	1,313	107	1,420	Mfg
Flat steel products	410	311	720	Mfg
Treated steel flat products	641	448	1,089	Mfg
Cement	205	4	209	Mfg
Clinker	364	0	364	Mfg
Lime	89	0	89	Mfg
Ammonia	134	168	302	Mfg
Ammonium nitrate	175	26	200	Mfg
Ammonium phosphate	894	252	1,146	Mfg
Urea	1,844	3	1,846	Mfg
Sodium cyanide	5	4	9	Mfg
Alumina	46	8,298	8,344	Mfg
Aluminium	214	5,167	5,381	Mfg
Bauxite	2	1,681	1,683	Res
Flat glass	731	26	757	Mfg
Glass containers	166	35	201	Mfg
Pulp and paper	1,027	868	1,895	Mfg
Polyethylene	707	0	707	Mfg
LNG	1	74,572	74,573	Res
Refined petroleum	54,899	4,219	59,118	Mfg
Coal	354	102,012	102,366	Res
Crude oil	8,274	11,564	19,838	Res
Ethane and LPG	359	2,137	2,496	Res
Iron ore	190	135,985	136,175	Res
Basic non-ferrous metal	107	1,041	1,148	Mfg
Nickel products	2	471	473	Mfg
Magnesia	13	-	13	Mfg
Manganese ore	22	1	23	Res
Ferro-manganese	12	0	12	Mfg
Silicomanganese	6	-	6	Mfg
Lithium ore	18	19,083	19,100	Res
Synthetic rutile	119	675	794	Mfg
Titanium dioxide	3	1	4	Mfg
Other metal ore	725	12,301	13,026	Res
Silicon	62	159	221	Mfg
Ethanol and dried distillers grain	87	709	796	Mfg
Lithium hydroxide	9	43	52	Mfg
Phosphoric acid	22	0	22	Mfg
Rare earth oxides	N/A	N/A	N/A	Mfg
Renewable diesel	N/A	N/A	N/A	Mfg
Renewable aviation kerosene	N/A	N/A	N/A	Mfg

Table 6 - Additional trade data - categories

Commodity	2023 Import value ($m AUD)	2023 Export value ($m AUD)	Total trade ($m AUD)
Total Trade	413,948	557,553	971,501
Total Safeguard Covered trade	74,298	382,429	456,727
SG trade flow share of total trade flow	18%	69%	47%
SG trade flow share of SG trade	16%	84%	100%
Manufacturing (A$ million)	64,354	23,093	87,447
% Manufacturing in SG covered	74%	26%	100%
Manufacturing, excluding refined petroleum (A$ million)	9,454	18,875	28,329
% of Manufacturing, excluding refined petroleum	33%	67%	100%
Non-manufacturing (A$ million)	9,944	359,336	369,280
% of non-manufacturing in SG covered	3%	97%	100%

Table 7 – Estimated emissions in Australian trade (average 2019 – 2023)[24], Mt CO_2-e[25]

Potential BCA sectors

ANZSIC Group	Comprising Safeguard Mechanism-covered goods	Emissions in imports	Emissions in exports
Basic Chemical Manufacturing	Ammonia, Ammonium nitrate, Ammonium phosphate, Sodium cyanide, Synthetic rutile, Titanium dioxide	2	1
Basic Ferrous Metal Manufact uring	Crude steel, Flat steel products, Long steel products, Treated flat steel, Ferro-manganese, Silicomanganese	1	1
Cement, Lime, Plaster and Con crete Product Manufacturing	Cement, Clinker, Lime	4	<1
Glass and Glass Product Manu facturing	Flat glass, Glass containers	<1	<1
Potential BCA sectors Total:		**6**	**2**

Other Safeguard Mechanism sectors

ANZSIC Group	Comprising Safeguard Mechanism-covered goods	Emissions in imports	Emissions in exports
Basic Non-Ferrous Metal Manufacturing	Alumina, Aluminium, Basic non-ferrous metal, Nickel products, Silicon	<1	13
Basic Polymer Manufacturing	Polyethylene	<1	<1
Coal Mining	Coal	<1	26
Grain Mill and Cereal Product Manufacturing	Ethanol and dried distillers grain	<1	<1
Metal Ore Mining	Bauxite, Iron ore, Lithium ore, Manganese ore, Other metal ore	<1	10
Oil and Gas Extraction	Crude oil, Ethane and LPG, LNG	2	15
Other Non-Metallic Mineral Product Man ufacturing	Magnesia	<1	0
Petroleum and Coal Product Manufacturing	Refined petroleum	8	1
Pulp, Paper and Paperboard M anufacturing	Pulp and paper	<1	1
Other Safeguard Mechanism sectors Total:		**11**	**65**
Grand Total		**17**	**67**

[24] Imports from foreign producers are assumed to have the same emissions intensity as Australian producers

[25] Emissions in exports represent total scope 1 emissions from Safeguard Mechanism-covered facilities in 2023. Trade volume is sourced from UN Comtrade. It is an average trade volume over the years 2019 to 2023 to account for volatility.