What can we learn about industries' vulnerability to overseas price shocks from Merchandise trade data in BLADE?[1]

Productivity Commission, March 2023

Australia faces inflationary pressures from supply chain shocks abroad, inflation abroad that may not be fully reflected in exchange rates, and a period of loose domestic monetary policy. The combination makes it difficult to identify which products and services may be affected by inflation. It is particularly difficult to identify the impact of supply chain shocks, as they lead to large changes in relative prices: for example, the Ukraine war has caused price spikes in gas and oil, barley and wheat. Understanding the impact of these overseas price shocks require us to understand the exposure of different industries: which industries use those products, and how sensitive the industry is to a price shock.

A large literature beginning with Dornbusch (1987) and Krugman (1987) explored how international shocks affect domestic prices. Much of this literature focused on how much of an exchange rate shock passes through to domestic prices. As a result, some papers have compared the impact of the broad-based exchange rate shock on different industries, according to their share of foreign firms and the intensity of competition (Amiti et al 2014, Feenstra et al. 1996, Goldberg and Campa 2010, Pennings 1991). Nakamura and Zerom (2010) looked at the impact an exchange rate shock or a shock to the cost of a key input has on a specific industry. The literature has not looked at the impact of shocks on the cost of specific products across multiple industries.

Australia does not have a dataset that collects input and output data from its manufacturing firms, unlike some other countries. Such manufacturing-based datasets are increasingly less representative, however, as the service sector grows in importance worldwide. This paper

1 BLADE disclaimer. The results of these studies are based, in part, on Australian Business Registrar (ABR) data supplied by the Registrar to the ABS under A New Tax System (Australian Business Number) Act 1999 and tax data supplied by the ATO to the ABS under the Taxation Administration Act 1953. These require that such data is only used for the purpose of carrying out functions of the ABS. No individual information collected under the Census and Statistics Act 1905 is provided back to the Registrar or ATO for administrative or regulatory purposes. Any discussion of data limitations or weaknesses is in the context of using the data for statistical purposes, and is not related to the ability of the data to support the ABR or ATO's core operational requirements. Legislative requirements to ensure privacy and secrecy of these data have been followed. Source data are de-identified and so data about specific individuals or firms has not been viewed in conducting this analysis. In accordance with the Census and Statistics Act 1905, results have been treated where necessary to ensure that they are not likely to enable identification of a particular person or organisation.

introduces an alternative Australian dataset that provides insight into the use of inputs in different industries, and the likely impact of a cost shock on each of those industries.

The Merchandise imports and exports data collected by the Department of Foreign Affairs and Trade (DFAT) is integrated into the Business Longitudinal Analysis Data Environment (BLADE) dataset.[2] While the dataset has some limitations, it is an improvement on past datasets and allows us to identify the industries that use a particular type of input heavily. It can also allow us to estimate how elastic the demand is for that input.

The first section of this paper presents analysis of input use by industry from 2017-2018 Merchandise trade data in BLADE, updating the analysis in our *Vulnerable Supply Chains* report (2021). The second part of the paper estimates demand elasticity for selected products using Merchandise trade data that was made available to the Commission during the *Vulnerable Supply Chains* report. We provide some case studies of specific vulnerable imports, but the methodology is applicable to any import.

Vulnerable imports are the appropriate focus for an analysis of potential disruptions in supply as they are more likely than other imports to be impacted by events in specific countries. In the event of a shock, policymakers need to determine which industries are most exposed to risk because of their dependence on vulnerable products.

To analyse inflation, a larger set of imported goods are of interest, because non-vulnerable imports can still be subject to price shocks and can still impact prices in some economically significant industries. A price shock to a core input such as petroleum may impact several important industries, even though petroleum products are not vulnerable because they are sourced from numerous countries. And policymakers may still need to know which industries are most exposed to surging overseas inflation, particularly if prices are rising at different rates for different goods.

For either type of policy question – which industries are at risk due to supply chain disruptions and which industries are exposed to overseas inflation - the analysis proceeds in a similar fashion. The merchandise trade data can in principle be used to identify how much of a product is imported by each Australian firm, and other components of BLADE makes it possible to identify which industry each importing firm belongs to. Then the merchandise trade data can be used to identify the demand elasticity of a product in each industry, through observing how demand changes in response to price changes.

Our analysis confirms that chemicals and personal protective equipment are the most likely categories of vulnerable imports to cause serious disruptions to an essential industry. While some other imports are both vulnerable and economically significant, such as laptop computers, they are primarily capital goods and their disruption would not cause a short-term crisis. Moreover, our estimates of the total elasticity of demand for six selected chemicals suggests that for several of these, the elasticity is significantly different from zero, suggesting that the economy has the ability to substitute away from the use of those

[2] See Appendix D for a more detailed description of BLADE.

chemicals or from the use of the products or services that use those chemicals. Analysis at the industry level may reveal a greater dependency on selected chemicals.

BLADE data has limitations for both analyses, however. One of the most significant is that some firms do not import their products directly, but instead use intermediaries.

If BLADE has limitations for analysing price shocks and inflation shocks, should Australia respond by developing new data sources? Given the declining importance of manufacturing in many OECD countries, a Census of Manufacturing seems unlikely to deliver maximum benefits. On the contrary, it may be advantageous that Australia is not tied to a large-scale survey focused on manufacturing. It is worth identifying what type of survey of inputs and outputs might be best suited for a modern service-oriented economy. We conclude by briefly discussing this question.

1. Identifying which industries uses specific imports

We outline the methodology for identifying which industries use a specific import such as petroleum. We do so by using vulnerable imports as an example: we identify vulnerable imports used by essential industries. But the methodology would be the same for analysing any import of interest.

Data

The Merchandise Imports and Clearances data collected by the Department of Foreign Affairs and Trade provides monthly observations of each product imported through Australia's ports and airports. An observation includes the product's 10-digit Harmonised Tariff Item Statistical Code (HTISC), the port of arrival, the weight and total price (both including and excluding customs insurance and freight) and the importing firm's Australian Business Number (ABN).

The analysis in Section 1 was undertaken using the Merchandise Imports and Clearances data for 2017-2018 in BLADE, and the analysis in Section 2 uses unpublished Merchandise Imports and Clearances data from 2010 to 2019 obtained directly from the ABS. The latter dataset did not include the importing firm's ABN.

Vulnerable imports

In our report on *Vulnerable Supply Chains* (PC 2021), 2016-2017 Merchandise Imports and Clearances data was used to identify vulnerable imports.

Following the previous report (PC 2021) an import is defined as vulnerable if more than 80% of Australia's imports are from a single country, ***and*** if global trade in the product is highly concentrated by country[3] (the Herfindahl-Hirschman index is more than 3100 or a single exporting country has more than 50% market share), ***and*** if Australia imports from the nation that is the main global supplier.

The Commission concluded that the 8-digit HTISC level was on average the most accurate for identifying vulnerabilities. At the 10-digit level, there were too many categories that were close substitutes for each other; and a vulnerability identified in a 10-digit category might not be a real vulnerability.

In 2016-2017 there were 5862 types of imported goods at the 8-digit HTISC, of which 1327 were imported primarily from one country. The Commission identified 292 imports as vulnerable at the 8-digit HTISC level (PC 2021).

Vulnerable imports used in essential industries

The next section updates the 2021 report by analysing merchandise trade data from 2017-18, and utilises BLADE instead of identifying the Australian National Accounts Input-Output tables published by the ABS to determine which industries used vulnerable goods, as was done in 2021.

A **key data requirement** for the analysis of vulnerable imports in different industries is the ability to link imports data with industry information.

The data sets required from BLADE are:

- BLADE core, which is built from administrative data on all active businesses. The ABS assigns each firm a 4-digit Australia New Zealand Standard Industrial Classification (ANZSIC) code.
- Merchandise Imports and Clearances data. As described above, these categories are aggregated to the 8-digit level.

The main advantage of BLADE is that these two datasets are linked. The firm that imports a particular good can be identified. This allows for analysis at the firm level and industry level, including for firms of different sizes. Firms can also be analysed across years.

Classifying firms at the 4-digit ANZSIC level creates 506 different industries. From these industries, the Commission identified a subset we define as 'essential industries.' We identified 81 essential industries, outlined in Attachment A. This process necessarily

[3] To identify products for which the world trade was concentrated, the Commission used world trade data published by COMTRADE. Unfortunately this data is available only at the six-digit HTISC level. The Commission checked whether the six-digit HTISC category to which an import belonged was globally concentrated, in the sense that one country exported 50% or more of the product, or the Herfindahl-Hirschman index was above 3100 when each country was treated as one 'producer'.

involved some subjective judgement. As discussed in our report, the Commission was focused on “industries that are essential to life and limb” such as water, electricity, basic communications, retail banking, and health. (An analysis that was focused on the economic costs of an external shock might instead focus on industries that are large employers, such as construction.) We were also able to include retailers of products that are essential to life and limb, for example pharmacies and fuel service stations.

BLADE can then be used to identify which firms import the 292 vulnerable products, and what industries those firms belong to. (Analysis of other import categories of interest, such as wheat or gas, would proceed similarly.)

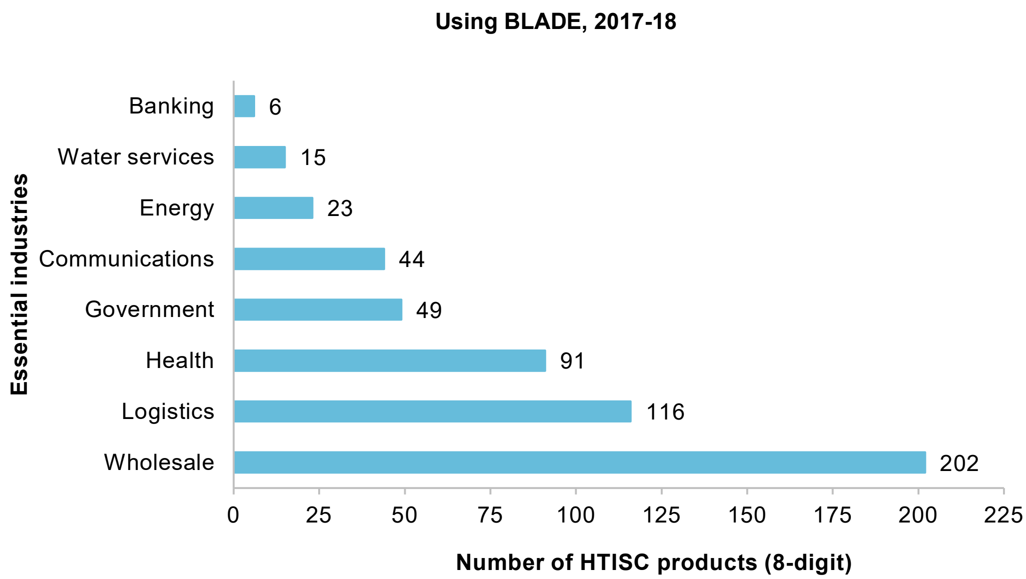
Identifying the importer’s industry in BLADE has significant advantages relative to the approach in the *Vulnerable Supply Chains* (2021) report, which used the Australian National Accounts Input-Output tables published by the ABS to determine which industries used vulnerable goods.[4] The input-output tables break the Australian economy down into 114 industries and only 114 categories of goods (instead of 5862). Therefore the input-output tables cannot conclusively identify which of the 114 industries use a specific eight-digit HTISC product. As a result, strong assumptions have to be imposed, such as assuming that the use of an eight-digit HTISC is proportional to the use of the broader industry’s products that it belongs to. Also, the essential industries included some sub-industries that are unlikely to be essential. For example, using 4-digit ANZSIC codes one can select ‘Banking’ (6221) as an essential industry, because a collapse of retail banking would precipitate a crisis; but Financial Asset Investing (6240) can be excluded. In the Input-Output tables, in contrast, Finance is one industry that cannot be subdivided. Likewise, Retailing is one industry in the Input-Output tables, whereas with ANZSIC codes one can identify vital components such as pharmaceutical retailing (4271).

Results

Using BLADE, 223 of the 292 vulnerable products are identified as being imported by firms in essential industries. Figure 1 shows the number of vulnerable products used by essential industries when using BLADE (re-aggregating the 81 ANZSIC industries into eight essential industries).

[4] Australian National Accounts: Input-Output Tables, 2016-2017, Cat. No. 5209.0.55.001 (ABS).

Figure 1 **Number of vulnerable imports used in essential industries[a]**



[a] Wholesale industries is separated from logistics industries when using BLADE.

Data source: ABS (*Business Longitudinal Analysis Data Environment, BLADE*, Cat. no. 8178.0, Microdata.

Comparing the nature of the goods identified in this updated analysis with those in the *Vulnerable Supply Chains* report, it would appear that BLADE is slightly better at identifying potentially critical goods used in essential industries. For example, in health the BLADE analysis identifies a larger array of chemicals including, iodine, ketone-phenols, etc. Reassuringly, the BLADE analysis also finds that a variety of food stuffs that were identified as vulnerable in the original work, such as catfish and mushrooms, are not actually used in essential industries.[5]

Table 1 presents the complete list of vulnerable imports for one industry, hospitals (ANZSIC 8401), as an example. More generally, across industries, an inspection of the list of goods identified by the BLADE analysis confirms that **chemicals** and **personal protective equipment** are the most obvious categories of goods that might be both vulnerable, used in essential industries, and critical to the functioning of those industries. In other words, these products may be used by essential industries such as hospitals, and a short-term disruption in their supply could be very serious. The first two products in Table 1 correspond to personal protective equipment.

The analysis still identifies vulnerable products used by essential industries that are not actually important to the operation of those industries, such as statuettes and wrist watches. Common-sense or analysis of elasticities of demand (as outlined in the next section) is

[5] The ABS omits some transactions in BLADE for confidentiality reasons. However the ABS has tables that give an approximation of how much each industry is affected by these omissions.

needed to eliminate a number of products that would be dispensable in the event of disruptions in supply or strong inflation.

Table 1 **All vulnerable imports purchased directly by hospitals (excluding psychiatric hospitals) (ANZSIC 84021), 2017-18**

HTISC code	HTISC description
39262029	Garments, of plastics or of other materials of HS 3901 to HS 3914 (excl. corset busks; & anti-radiation suits, anti-contamination suits & similar protective garments; & goods of HS 9619)
39262090	Articles of apparel & clothing accessories (incl. gloves, mittens & mitts) of plastics or of other materials of HS 3901 to 3914 (excl. corset busks; garments; anti-radiation or anti-contamination suits & sim protective garments; & HS 9619)
49090000	Printed postcards, personal greeting cards, message & announcement cards, whether or not illustrated
61159610	Socks, ankle-socks, sockettes & the like knitted or crocheted, of synthetic fibres (excl. graduated compression hosiery)
64029990	Footwear, with outer soles & uppers of rubber or plastic (excl. covering the ankle, metal toe-caps, thongs, waterproof, for sport, diving etc) not exceeding size 1, 2nd series
84713000	Portable automatic data processing machines, weighing not more than 10 kg consisting of at least a central processing unit, a keyboard & a display
85131000	Portable electric lamps designed to function by their own source of energy (eg dry batteries, accumulators, magnetos) (excl. lighting equipment of 8512)
85285200	Monitors, not incorporating television reception apparatus, capable of directly connecting to & designed for use with an automatic data processing machine of heading 8471 (excl. cathode-ray tube monitors)
96039000	Brooms, brushes (excl. roller squeegees); hand operated; mops, feather dusters & squeegees; mech floor sweepers, not motorised; prepared knots & tufts for brooms or brushmaking

Source: ABS (*Business Longitudinal Analysis Data Environment, BLADE*, Cat. no. 8178.0, Microdata).

Table 2 indicates all the vulnerable chemicals that are used by the human pharmaceutical and medicinal product manufacturing industry (ANZSIC 1841). This industry and these chemicals are obvious candidates for further exploration.

Table 2 **Chemical imports by the human pharmaceutical and medicinal product manufacturing industry (ANZSIC 1841), 2017-18**

HTISC code	*HTISC description*
28012000	Iodine
28362000	Disodium carbonate
29145000	Ketone-phenols & ketones with other oxygen function
29181400	Citric acid
29181600	Gluconic acid, its salts & esters
29214400	Diphenylamine & its derivatives; salts thereof
29223900	Amino-aldehydes, amino-ketones, amino-quinones & salts thereof (excl. those containing more than one kind of oxygen function, amfepramone (INN), methadone (INN), normethadone (INN) & salts thereof)
29336900	Heterocyclic compounds with nitrogen hetero-atom(s) only, containing an unfused triazine ring, whether or not hydrogenated, in the structure (excl. melamine, cyanuric acid & its derivatives & atrazine)
29381000	Rutoside (rutin) & its derivatives
29394200	Pseudoephedrine (INN) & its salts

Source: ABS (*Business Longitudinal Analysis Data Environment, BLADE*, Cat. no. 8178.0, Microdata).

Some of the vulnerable products identified seem important to production, but they are capital goods, or inputs to capital goods. This includes laptop computers; receivers; safety glass; monitors; and specialised lamps. Firms usually have more ability to substitute around capital goods than intermediate goods (PC 2021). Faced with a shortage of a capital good, a firm can use existing capital goods more intensively, or it can invest more in repairing existing capital goods. For example, mining companies have been known to resurrect old tyres from dumping groups during periods of shortages of tyres for large mining equipment. As a result, an interruption in supply of these products would be less likely to precipitate a crisis. As to whether a price spike in capital goods (or an input to capital goods) is likely to generate significant inflation, it would depend on whether the price spike is likely to be long-lasting or permanent. Firms have more ability to postpone purchases of capital goods than purchases of intermediate goods.

Limitations of BLADE

Despite these benefits, BLADE data also has weaknesses. The most important weakness is that many products are not imported directly by firms, but by wholesalers. As a result, given that BLADE identifies the importing firm, it is not always possible to identify the firm that will be ultimately using the import as an input into essential products or services.

The ‘wholesale’ category includes a broad range of firms. Wholesale is defined as firms that buy intermediary and finished products but do not own the means of production. It includes import merchants and wholesalers whose primary focus is domestic wholesale. It also includes a large range of companies that design, test and develop products in Australia and have them produced overseas.

Products imported by “the wholesale industry” may be destined to any industry, or directly to the retail market. Thus excluding wholesalers would provide an incomplete picture of the dependence of an industry on any particular imports. For example, the list in Table 1 is unlikely to include all vulnerable imports used in hospitals. Taking vulnerable imports in essential industries as an example shows that wholesalers play a significant role:

- Analysing all wholesale industries reveals that wholesalers import 48 per cent of each vulnerable product on average, but this differs by product type.

- Of the 292 vulnerable products, 223 of them are imported by firms in essential industries, and 202 are imported by wholesalers (Figure 1). Thus imports through wholesalers feature in almost every vulnerable product category.

More research is needed on the role of wholesalers on the Australian end of the supply chain. It may be that some industries commonly import all of their inputs directly, whereas other industries use intermediaries. Exploring the patterns in the data while using information obtained directly from an industry about its input usage would be valuable.

Furthermore, if a product is commonly imported by one industry and resold to other industries, the merchandise trade data will not reflect the final user of the product. Petroleum is one product that might well be of interest, given the recent fluctuations in oil prices. But refined petroleum is mainly imported by the large petrol retailers, and then sold to other industries. Petroleum import data will not provide much information on the final industry using the product.

Another issue is that larger firms may be involved in several lines of business. Thus the ANZSIC classification of a large firm may not reflect all of the industries the firm is involved in, and could result in some significant distortions (McMillan and Burns 2021).

2. Identifying the effect of a rising import price on an industry of interest

To determine the impact that a spike in an import price will have on the economy, the first step is identifying which industries use the import. The next step is to measure how much of the import price shock will pass through to prices in that industry’s products or services. The impact of a price shock will depend on three features:

1) What is the share of this input in the total cost of the industry’s products?
2) What ability does the industry have to substitute away from this input, either through using alternative inputs, or re-designing processes?
3) Are consumers able to substitute away from this product?

Share of the import in firm costs

The first question can be answered quite easily. Given that BLADE includes tax declarations from the firm on its annual revenues and costs, as reported to the Australian Taxation Office, and the Merchandise Trade data indicates the value of imports to those firms, it is a straightforward matter to identify the cost share of a particular import.[6] This provides a first rough measure of cost pass-through. For example:

- if the import forms 25% of total costs
- and there is inflation of X% in the value of that import

then the firm's costs should rise by 0.25*X%, if the firm is unable to make any change to its production process and it passes on the cost increase. The share of total costs represented by this import give an idea of how significant the import price rise could be for the industry. Some imports may be a major share of costs, and others a very small share of costs: contrast for example diesel fuel for the trucking industry with surgical gowns for a hospital.

Demand elasticity

The second and third questions are essentially about the elasticity of demand for the input and for the final product. What happens to firms' demand for this input in a particular industry when the price rises?

An elasticity of demand that is well below zero for an imported input would imply either (2) that firms in this industry will find substitutes for the input when its price rises, or (3) that demand for this industry's final product or service is elastic, and demand falls when the final product's price rises as a result of rising input costs. Either possibility implies that there will be no significant price increase for consumers, either because the industry can make substitutions in their production process, or because consumers can make substitutions in their consumption. And as a result, cost pass-through would be lower, and any interruptions to supply of that import may have a limited impact on inflation.

But an elasticity of demand close to zero implies that firms have little ability to substitute away from this input, and the final product or service is essential. Cost pass-through would be as described in the paragraph above, and any interruptions to supply (such as a shortage of Personal Protective Equipment, or a delay in the delivery of a life-saving drug) would have real effects on the availability of the goods in question.

There is one caveat: if the firms in this industry have market power, then these conclusions would be softened, and pass-through would be less, even if there was no ability to substitute

6 In practice, however, "costs" as reported to the Australian Taxation Office can reflect tax-minimising practices rather than the production process. Costs will also include investment costs rather than merely production costs, and the distinction is not always clear. This can produce misleading results. One possible solution is to measure expenditure on this input as a share of *revenue* rather than *cost*, as there is generally less discretion in the timing of revenues than costs.

away from this input. In equilibrium, firms with market power tend to pass on less than the full increase in their marginal cost.

Demand elasticity and exogeneity assumptions

The perpetual challenge in estimating demand elasticities is to find a price change that is independent of other factors that affect demand; otherwise estimates may be biased. We adopt the assumption that Australia is a price taker in the global market and therefore the world price is independent of unobservable factors affecting Australian demand. The logic is that Australia is a small participant in the world market and so changes to Australian demand should *not* affect world prices. For example, if Japan is a large importer of iodine, and a demand shock in Japan reduces iodine imports significantly, this would cause the world price to decrease. But the demand shock in Japan is unlikely to affect the demand for iodine in Australia directly — only indirectly via the decrease in the world price. The Australian market's response to the price decrease in iodine could then be used to estimate the price elasticity of demand for iodine.

This logic will not always be true; some unobserved factors may affect both Australian demand directly and world prices. For example, if Japan increased its imports of iodine due to a newly-discovered use that also affected Australia, then the Australian, Japanese and world demand will be directly affected by this technological advancement and world prices would increase. Unobserved factors that influence both the world price and Australian demand directly like this introduce bias into estimates of price elasticities. Thus the analysis should be supplemented with industry-specific information on any major trends.

Estimating elasticities of Australian demand for selected chemicals

In this section we demonstrate below how to calculate the elasticity of ***total*** Australian demand for several products. Estimating the demand elasticity for a specific ***industry*** would proceed with the same methodology, but restricting attention to imports from firms in the industry of interest rather than total Australian imports.

Using Merchandise import data (in this case, data obtained directly from the ABS rather than through BLADE), we estimate price elasticities of demand for selected chemicals — one of the main categories of essential and vulnerable goods identified in the Commission's study on *Vulnerable Supply Chains* (2021). We focus on four vulnerable chemicals among the ones with more frequent observations of imports: disodium carbonate and citric acid (see Table 3), glycine derivatives, and melamine. The uses of these chemicals are described in Box 2. In Appendix C we also undertake some estimation of elasticities of demand for two chemicals that are not classified as vulnerable: calcium chloride and magnesium sulphate. Both are in high demand (see Table 3), which improves the reliability of estimates.

Table 3– Chemicals with a ‘high volume’ of quarterly observations (not all of which are vulnerable imports)

Chemical name	Number of observations	Mean quantity (tonnes)	Mean price ($)	Mean value ($’000) (price*quantity)
Calcium chloride	2603	61	163.4	9896
Citric acid	2266	53	170.1	9019
Magnesium sulphate	1996	86	10.7	925
Disodium carbonate	1720	1316	8.1	10663
Potassium phosphates	1349	21	287.9	5921
Cyanuric acid and its derivatives	1258	25	142.1	3540
Gluconic acid, its salts and esters	1170	43	10.8	469
Ketone-phenols and ketones with other oxygen function	942	2	1899.3	4692
Ammonium chloride	823	52	90.8	4759
Silicon carbide, whether or not chemically defined	781	27	1200	31967
Aromatic ethers and their halogenated, sulphonated, nitrated or nitrosated derivatives	714	6	271.8	1631
Artificial corundum, chemically defined	653	46	3.4	159

a. Chemicals were defined as ‘high-volume’ if they contained at least 10 transactions in each quarter and had at least nine years of quarterly data. Mean quantity, price and value are the averages across all transactions for a given chemical. These estimates can be biased by extreme outliers. For example, the mean price for citric acid is $170.1, but quarterly means generally are below $20; there are a few high-priced quarters that push the mean up.

Source: ABS (*Merchandise Imports and Import Clearances*, 2010-2019, unpublished).

Box 2 **Uses of selected chemicals**

Disodium carbonate

Sodium carbonate, commonly known as soda ash, is an easily-produced and versatile compound. It is commonly used in the manufacture of glass, detergent, soap, paper and as a food additive. It is also used in water treatment as a pH corrector for the protection of water infrastructure. In 2018, global trade in sodium carbonate was worth US$3.7 billion, with major suppliers including the United States (40 per cent), Turkey (17 per cent) and China (10 per cent). Australian imports accounted for 1.8 per cent of world trade.

Citric acid

Citric acid has a number of properties that make it useful in many applications across manufacturing. It is commonly used to give a tart, sour or acidic flavour to manufactured foods and beverages. It is also used as an acidity regulator, a preservative and antimicrobial agent. In 2018, global trade in citric acid was worth US$1.5 billion, with major suppliers including China (48 per cent) and Austria (16 per cent). Australian imports accounted for 0.7 per cent of world trade.

Glycine derivatives

Glycine derivatives are amino acids that are used in some medicines and as a pesticide. In 2018, global trade in glycine derivatives (captured within 'organo-inorganic compounds: other than tetramethyl lead, tetraethyl lead, and tributyltin compounds' in the 6-digit HS classification) was worth US$7.4 billion. Major suppliers include China (41 per cent), the United States (18 per cent) and Germany (12 per cent). Australian imports accounted for 2.2 per cent of world trade.

Melamine

Melamine is a compound used mainly in the manufacture of plastics, lacquers, adhesives, and insulation. It is also used in paints, textiles and wallpapers due to its fire retardant properties. In 2018, global trade in melamine was worth US$1.2 billion, with major suppliers including China (42 per cent), Germany (13 per cent) and the Netherlands (12 per cent). Australian imports accounted for 3 per cent of world trade.

Sources: Chemical book (2016); CEPII (2021); Observatory of Economic Complexity (2019b).

Chemicals are relatively homogenous products

An elasticity can only be usefully estimated with homogenous goods. If goods are differentiated, then the estimates will be affected by changes in the composition of what is imported, rather than just changes in prices. Chemicals are likely to be more homogenous within a category than many other types of goods, such as clothing or specialised equipment.

Unfortunately, even a chemical import is not necessarily homogenous. There are four main dimensions of differentiation.

First, while the date of arrival into Australia is recorded, the date of purchase of the shipment is not recorded; thus the purchases arriving in January 2010 may have been purchased at different times, when the market prices were different. Thus the "law of one price" may hold, but the price on arrival will reflect multiple prices.

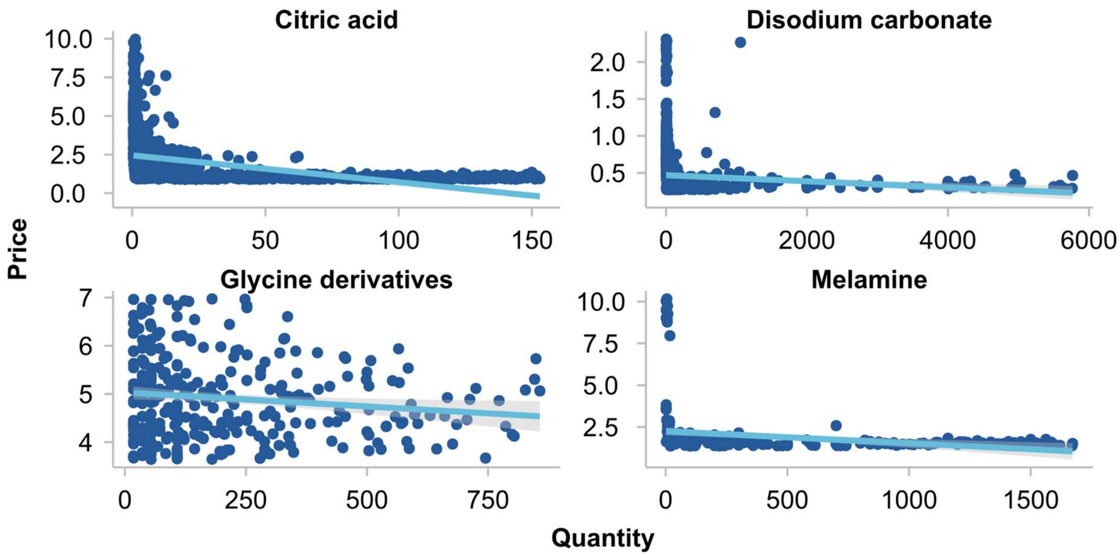
Second, some buyers will be purchasing under long-term contracts and may face very different prices to those purchasing on the spot market. There is no way to distinguish 'spot prices' and 'long-term contract prices' in this data.

Third, there are likely to be volume discounts offered by the supplier of the chemical, as any shipment will involve some fixed costs. The prices of larger shipments are noticeably lower and a regression confirms that there is a negative price-volume relationship (Figure 2). Prices can be up to ten times larger for small shipments. This effect will be particularly noticeable with shipments sent by air, which could arguably be considered a different product (involving very different fixed costs for the shipper). As a result, we have dropped air shipments from the estimation.

Fourth, while a chemical is homogenous at the molecule level, it may be sold in different concentrations. The large variation in prices that we observe might indicate some heterogeneity in the products recorded. For example, a chemical could be sold in different concentrations, which would be reflected in their prices. While there is clustering around the weighted average price for some chemicals (Figure 3), there is still a lot of variation for what is assumed to be a homogenous group of products — or at least a group whose mix does not change markedly.

Figure 22 – Bulk discounting in chemical imports[a]

Scatterplot of price (per kg) by quantity of transaction (tonnes) for each chemical, 2010-2019



[a] The bottom and top deciles of transactions were filtered out for both price and quantity to improve the readability of the figure.

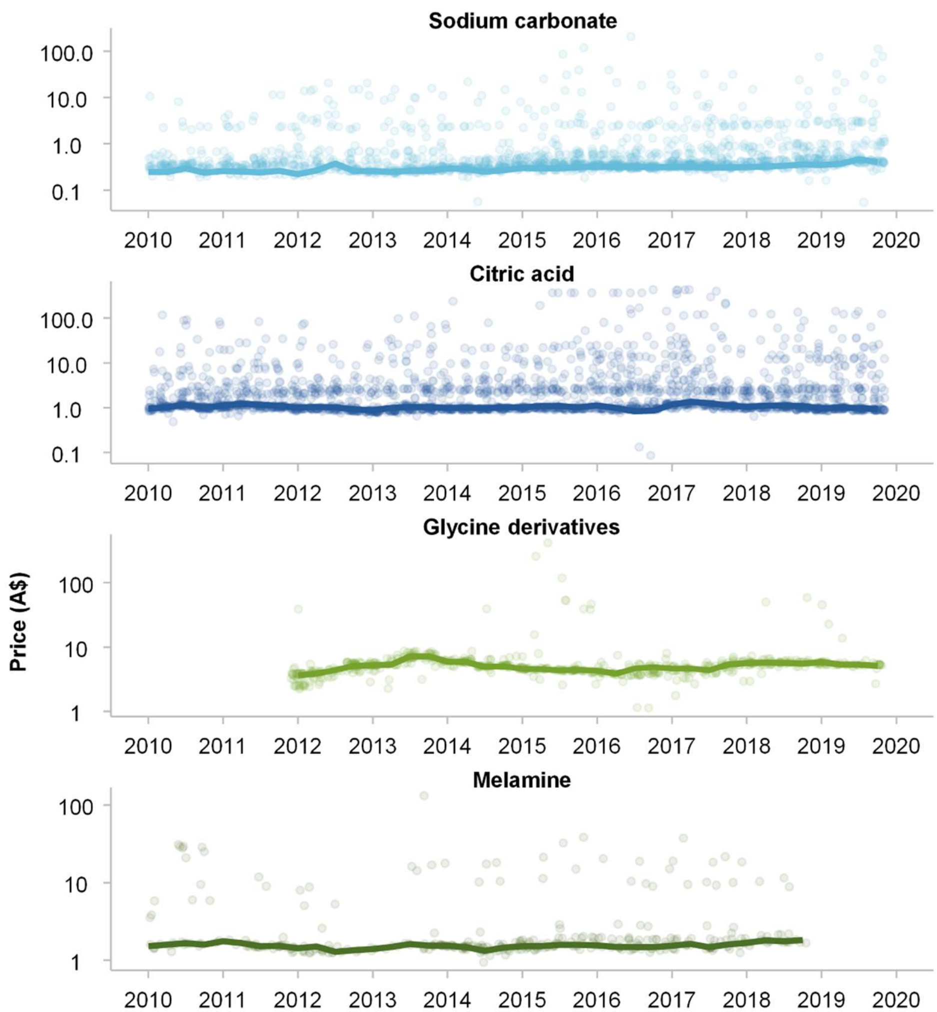
Source: ABS (Merchandise Imports and Import Clearances, 2010-2019, unpublished).

We aggregate the monthly ABS imports data into quarters (and into months for some of the regressions for which more data is available). We derive unit values (prices) by dividing the good's value (including insurance and freight) by its quantity. We then construct a weighted average price using quantity as the weights to create a price variable that accurately reflects the majority of purchases.

The four chemicals analysed here show a seasonal pattern in their demand (Figure 4), so we include seasonal dummies in most of the regressions.

Figure 3 Prices of chemicals vary

Jitter plot[a] of prices (as individual circles) [b,c] and weighted average price (solid line)[d] ($AUD) from 2010 to 2019

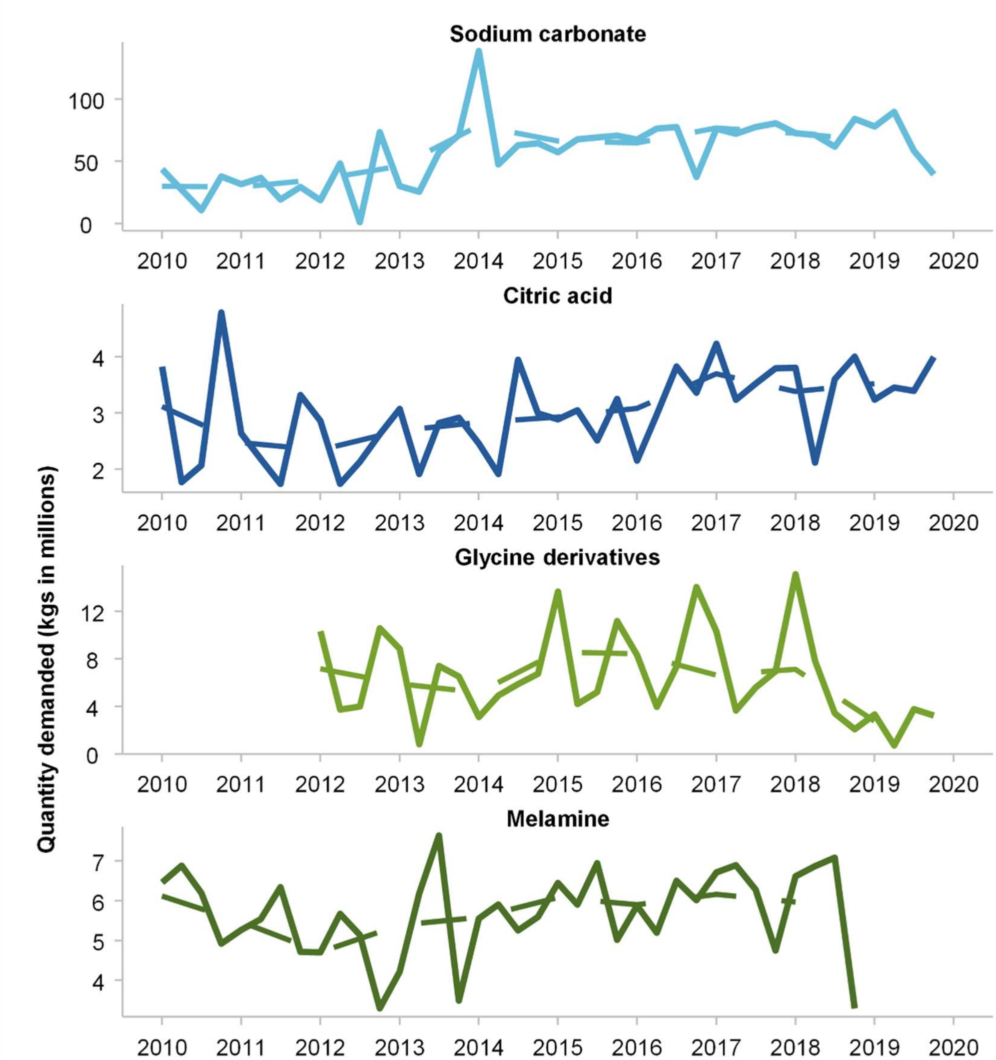


[a] Jitter plots slightly perturb each point. [b] Prices are unit values, derived from cost (including insurance and freight, CIF) divided by quantity. [c] Prices presented on a log scale and outliers over $AUD1000 have been removed for readability. [d] Weighted average price is denoted by the solid line.

Source: ABS (*Merchandise Imports and Import Clearances*, 2020, unpublished).

Figure 4 **Chemicals have annual and quarterly patterns**

Kilograms (in millions) imported to Australia, quarterly for 2010 to 2019[a]



[a] The dashed line represents the average quarterly imports for the year.

Data source: ABS (*Merchandise Imports and Import Clearances*, 2020, unpublished).

Autocorrelation and cointegration properties of the data

In principle elasticity could be estimated by simply regressing log quantity on log price but prices and quantities exhibit substantial correlation over time. An augmented Dickey-Fuller test shows that stationarity of both weighted average price and total quantity can be rejected, while it cannot be rejected that first differences of these series are stationary.

We estimate demand elasticities for the four chemicals using two techniques that control for autocorrelation in the data: an autoregressive distributed lag model (ARDL), and, because the variables in the model are both stationary and cointegrated, we also estimate an error-correction model (ECM) (see Appendix B for cointegration and stationarity results for citric acid). The results from both models are very similar.

Autoregressive distributed lag models

ARDL is a time series model which predicts current values of a dependent variable based on both current and lagged variables of the dependent and independent variables. ARDL is particularly useful when variables are integrated at different orders. The following ARDL equation (for log variables) is used to estimate demand elasticity for citric acid.

$$logQ_t = \beta_0 + \beta_1 logP_t + \beta_2 M_t + \sum_{i=1}^{p} \delta_i \, logQ_{t-i} + \sum_{i=1}^{q} \gamma_i \, logP_{t-i} + \sum_{i=1}^{z} \pi_i \, M_{t-i} + \gamma_t + \epsilon_t \qquad (1)$$

Where:

- Q_t is quantity demanded at time t
- β_0 is the constant
- β_1 is the **coefficient of interest** and shows the short-run price elasticity of demand, which measures the percentage change in quantity demanded resulting from a 1% change in price
- β_2 controls for current levels of the activity variable (in this case, log of aggregate food expenditure)
- δ_i are the autoregressive lags for the log quantity of citric acid imported at time period t-I
- γ_i are the lagged coefficients for log price at time t-i
- π_i are the lagged coefficients for the log activity variable at time t-i
- γ_t includes monthly dummy variables to control for seasonality
- ϵ_t is the error term.

The activity variable is intended to capture exogenous shifts in demand that might affect the precision of the elasticity estimate. In the case of citric acid, a food additive, any exogenous changes that affected total expenditure on food might reasonably affect demand for citric acid. As a result, we include food expenditure (and in some specifications, lags of food expenditure) as an explanatory variable. Food expenditure is only available quarterly; thus it was assumed to grow at a constant rate over the quarter in order to generate monthly observations from the quarterly data.

Care must be taken in choosing the activity variable as it should not be a proxy for the size of the specific industry of interest. For some inputs, such as diesel for the trucking industry, a price shock would impact the price of trucking overall and reduce the size of the industry. Including a measure of the size of the trucking industry in the regression would lead to an underestimate of the demand elasticity.

Table 4 presents the results with monthly variables, while Appendix C contains results when weighted price and quantity observations are constructed for each quarter. Results in Appendix C are similar but less statistically significant, given the limited number of quarter observations. Using exchange rates as the activity variable yields similar regression results as well.

The following model specifications were estimated (see Table 4 for results):

1. equation 1 with a lag length of one and without the activity variable (M_t)
2. equation 1 with a lag length of one and with the activity variable
3. equation 1 with optimal lag length for each variable determined by the Akaike Criterion (AIC), and without the activity variable
4. equation 1 with optimal AIC lag length for each variable and with the activity variable.

All of these specifications included month dummies.

Table 4 – ARDL model results for Citric Acid at a monthly level[a]

Coefficient	Specification 1	Specification 2	Specification 3	Specification 4
P_t	-1.05*** (0.32)	-0.94*** (0.36)	-0.86** (0.33)	-0.78** (0.36)
M_t		1.93 (11.51)		-21.97 (23.20)
Q_{t-1}	0.34 (0.10)	0.24 (0.11)		
Q_{t-2}				
Q_{t-3}				
P_{t-1}	0.77** (0.32)	0.64 (0.33)	0.27 (0.34)	-0.20 (0.34)
M_{t-1}		-0.86 (11.49)		48.34 (32.29)
N	**119**	**110**	**118**	**101**
R-squared	**0.23**	**0.28**	**0.17**	**0.29**

a. Data ranged from 2010 to 2019. The optimal number of lags for food expenditure was 9 (only one lag is reported in table), for price was 2 (only one reported in the table), and no lags for quantity. The specifications that include food expenditure had less observations because data were only available up to the 1st quarter of 2019. Standard errors presented in parentheses. *** p<.01 ** p<.05 * p<.1

Sources: ABS (*Merchandise Imports and Import Clearances*, 2010-2019, unpublished); ABS (*Australian National Accounts: National Income, Expenditure and Product*, December 2022, Cat. no. 5206.0, table 8).

The results show that a one per cent increase in the current price of citric acid would lead to a -0.78 to -1.05 per cent decrease in quantity demanded. Given the standard errors, it cannot be determined whether the elasticity of citric acid is greater or less than (-1) (i.e. elastic or inelastic), and it appears to be inelastic when taking into account that some of the price adjustment may occur with delay (i.e. accounting for the effect of P_{t-1}). When allowing for a slower adjustment to prices, with the lagged term, the coefficient on demand for citric acid is different from zero (Equation 1). But the ARDL structure is not ideal for identifying the long-term adjustment to prices; we will consider an error correction model next.

The coefficient on the activity variable (food expenditure M_t) is not statistically different from zero, and it is improbably large and improbably negative in equation 4. An elasticity of more than 1 seems unlikely. Most likely this is the result of the interpolation of food expenditure from quarterly to monthly, leading to imprecise estimates.

Appendix C outlines the results of ARDL regressions for the other three chemicals: disodium carbonate, glycine, and melamine. Again, the estimates of demand elasticities are relatively consistent across different methodologies. Appendix C also provides results for two chemicals with large numbers of shipments recorded: calcium chloride and magnesium sulphate.

Error Correction Models

An ECM corrects for non-stationarity and time trends in the data. The model regresses the first difference of the dependent variable on the first difference of the independent variable (the short-run effect), and the lag of the dependent and independent variables (the long-run effect). This estimation thus provides the long-run and short run dynamics of demand elasticity. The regression is:

$$\Delta logq_t = \beta_0 + \beta_1 \Delta logP_t + \beta_2 \Delta logM_t + \beta_3 logP_{t-1} + \beta_4 logq_{t-1} + \beta_5 logM_{t-1} + \gamma_t + \varepsilon_t \quad (2)$$

where:

- α_0 is the constant
- β_1 is the short-run price elasticity of demand
- β_2 controls for short-run changes in the activity variable
- β_3 , β_4 and β_5 are the lagged coefficients for log price, log quantity and log activity variable at time t-1. This allows for an adjustment to long-run equilibrium
- γ_t represents monthly dummy variables
- ϵ_t is the error term.

A more structural version of equation (2), which allows us to see the relationship between the short run and the long-run relationship, is:

$$\Delta logq_t = \alpha_0 + \beta_1 \Delta logP_t + \beta_2 \Delta \log M_t - \alpha_1 (logq_{t-1} - \frac{\alpha_2}{\alpha_1} logP_{t-1} - \frac{\alpha_3}{\alpha_1} logM_{t-1} - g) + \gamma_t + \varepsilon_t \qquad (3)$$

where the long run relationship is $logq_t = g + \alpha_2 \log P_t + \alpha_3 logM_t$
and $\alpha_1 = \beta_4, \alpha_2 = \beta_3, \alpha_3 = \beta_5, g = \frac{\beta_0 - \alpha_0}{\beta_4}$

The long-run part of the equation is represented by the brackets in equation 6. α_1 is the adjustment term which indicates how strongly import demand responds to deviations away from the long-run relationship. The short-run part of the equation is represented by the first differenced terms.

The following model specifications – with a lag length of 1 - are included in Table 5:

- Specification 1 – equation 2 with only β_1, β_3 and β_4
- Specification 2 – equation 2 with only β_1, β_3, β_4 and γ_t

The activity variable was not included in the monthly estimation, as food expenditure is a quarterly variable and it is not reasonable to interpolate it and first difference it. But we include it in quarterly estimation in Appendix C.

Table 5 – ECM results for Citric Acid at a monthly level[a]

Coefficient	Specification 1	Specification 2
$\Delta logP_t$	-1.15*** (0.30)	-1.05*** (0.34)
$logP_{t-1}$	-0.33 (0.31)	-0.28 (0.31)
$logq_{t-1}$	-0.64*** (0.09)	-0.66*** (0.10)
N	**119**	**119**
R-squared	**0.41**	**0.45**

a. Data ranged from 2010 to 2019. Standard errors presented in parentheses. *** p<.01 ** p<.05 * p<.1

Source: Commission estimates based on ABS (*Merchandise Imports and Import Clearances*, 2020, unpublished).

The ECM results suggest that there is correction towards the long-term relationship. Going by the interpretation in equation (3), the long-term elasticity of demand $\frac{\alpha_2}{\alpha_1}$ lies around -0.42. However, given that some of the coefficients in the regression are not significant, this estimate of long-term elasticity cannot be shown to be different from zero. The short-term elasticity is statistically different from zero. Thus the demand for citric acid could be inelastic, and further investigation is needed.

All specifications showed no autocorrelation according to the Durbin-Watson test.

The proposed technique has been used in other papers which estimate import cost pass-through. Nakamura and Zerom (2019) (based on Goldberg and Campa 2010) included a dependent variable in log differences, because of the autocorrelation in the data. They also included lags of the independent variable, to allow for any time lags in adjusting to changes in the independent variable. However, no lags of the dependent variable are included, axiomatically. Their inclusion in autoregressive models is fairly common, and the fact that the coefficient is significant in both specifications above suggest that its inclusion is important to the accuracy of the model.

The quarterly ECM for citric acid, disodium carbonate, glycine and melamine are available in Appendix C.

Limitations of the analysis

The fact that many firms buy imports from an intermediate industry (wholesalers and others) presents a challenge when estimating these elasticities. Another challenge in the estimation of an elasticity is that there may be domestic firms producing the same product, impacting the response to an import price shock.

In the presence of intermediaries, we may not be able to measure the amount imported by a particular industry. Consequently, the only sensible exercise may be to calculate an elasticity of total demand, rather than the demand elasticity of one industry. That exercise would still be useful for a product known to be used primarily by one industry, or if a product is used in a similar way in most industries. However, that assumption may not always be reasonable. For example, chlorine is imported to treat drinking water, an essential activity, and to treat water in swimming pools, which is nonessential; and the elasticity of demand is likely to be quite different for those sub-industries.

Local supply poses a separate challenge, as the dataset does not incorporate purchases of the product from local suppliers, and those purchases should change as well in response to an overseas price shock. The Merchandise trade data will also provide no indication as to whether there is a domestic source of supply; that information must be gathered from other sources.

3. Thoughts on new datasets

Census of manufacturing

The BLADE dataset, while remarkably useful in constructing an improved view of vulnerable imports, suffers from some limitations in the study of which industries use vulnerable imports, and in the study of the inflation impact of those imports. Only imported products, and the firms who first import them into Australia, are included in the merchandise trade data. As a result, BLADE cannot accurately capture the impact of an overseas price shock in one product on every Australian industry, as some industries will rely on intermediaries for their imports. And BLADE cannot capture domestic contagion, when a shock in one product price flows into other industries.

This places Australia at a disadvantage relative to other countries with more detailed manufacturing data. Even middle-income countries collect this data; for example Mexico collects input and output data annually from manufacturing firms in the Encuesta Industrial Annual, as does Indonesia in selected years. Such a census could be developed for Australia, but would only cover the approximately 5% of GDP covered by manufacturing. Such a survey would not provide a full picture of the economy, nor even of the industries that depend on overseas inputs. Sectors such as construction rely heavily on materials, and many essential services still rely on some products to deliver the service. General practitioner services in medicine, for example, rely critically on the availability of medicines and diagnostic test equipment. It would be more useful for the Australian Bureau of Statistics to develop a survey that covers manufacturing as well as the service sector, and that includes the non-market services of education, health, and government.

What types of data should be gathered in such a survey? A classification system for services of different types and skill levels is urgently needed. Firms could report on the prices charged for different services, and the wage bill for those services. And firms should report on their inputs, including any specialised services that they procure.

Price data

Lack of price data has posed consistent challenges for users of BLADE. While revenues and costs are available from tax information in BLADE, there are few volume measures in the dataset, and no price measures. Even measures such as wages that are common in other datasets are not available in BLADE; BLADE includes the total wage bill, and headcount, but no measure of which employees are full-time and which employees are part-time.[7] And there is no price information collected for the firm's output. As discussed by McMillan and Burns (2021):

[7] The Linked Employer-Employee Dataset LEED used internally by Treasury, which incorporates the information in BLADE and also in personal tax data, overcomes this particular challenge.

> This absence of price or volume information makes BLADE difficult to use for certain purposes, such as estimating firm-level productivity or mark-up. Usually, in order to estimate productivity changes over time, prices of output must be held constant to prevent non-productivity related issues from affecting measures of output. For example, if one does not hold prices constant then changes in output (measured in terms of revenue minus intermediate input costs) may reflect changes in consumer demand or the degree of competition in the market.

The experience of this paper suggests that the usefulness of price data can be overstated. Even a commodity such as a chemical import that should be homogenous (indeed identical at a molecular level) shows significant heterogeneity. The date that the order was placed, the length of the contractual relationship, the size of the shipment, and the concentration of the chemical can all influence the price that is paid. As a result, even with price data it will be difficult to be certain that a product's characteristics will remain constant over time. Short-run changes in price can be very informative about inflation; but in the longer run, there is the risk that the firm chooses to alter the characteristics of the product. Firms under cost pressure may reduce the quality of their product through various means. Firms may also raise prices by introducing and promoting new higher-quality products, with a higher margin, and eventually discontinuing the older product. Price data may allow for a correct estimate of markups (assuming that challenges in measuring capital costs can also be resolved), but there will continue to be challenges in measuring productivity.

Summary

The merchandise trade data in BLADE has significant advantages relative to the approach in the Vulnerable Supply Chains (2021) report, which used the Australian National Accounts Input-Output tables published by the ABS to determine which industries used vulnerable goods. This allows for a systematic scan of industries and products which are vulnerable to supply shocks.

This data can be linked to information about importing firms to provide some insight into the likely impacts of price shocks or interruptions in supply of selected overseas products. It is possible to determine market reactions to price shocks, but these insights are limited because Australia does not have detailed data on the inputs and outputs of domestic firms.

Australia may want to develop a regular survey of firms that measures their inputs and their outputs in detail. Given the small share of manufacturing in the economy, it is important for this survey to include all sectors of the economy, not simply manufacturing. It should include agriculture, mining, manufacturing and all services, including the growing non-market service sector (education, health, and government). And care should be taken in constructing any price measures of inputs and outputs.

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Appendix A: Essential industries selected at the ANZSIC 4-digit level

Essential industry	ANZSIC	ANZSIC description	Selected as Essential
Banking	6210	Central Banking	No
	6221	Banking	Yes
	6222	Building Society Operation	Yes
	6223	Credit Union Operation	No
	6229	Other Depository Financial Intermediation	No
	6230	Non-Depository Financing	No
	6240	Financial Asset Investing	No
Health	1841	Human Pharmaceutical and Medicinal Product Manufacturing	Yes
	1842	Veterinary Pharmaceutical and Medicinal Product Manufacturing	Yes
	8401	Hospitals (Except Psychiatric Hospitals)	Yes
	8402	Psychiatric Hospitals	Yes
	8511	General Practice Medical Services	Yes
	8512	Specialist Medical Services	Yes
	8520	Pathology and Diagnostic Imaging Services	Yes
	8531	Dental Services	Yes
	8532	Optometry and Optical Dispensing	Yes
	8533	Physiotherapy Services	Yes
	8534	Chiropractic and Osteopathic Services	Yes
	8539	Other Allied Health Services	Yes
	8591	Ambulance Services	Yes
	8599	Other Health Care Services n.e.c.	Yes
	8601	Aged Care Residential Services	Yes
	8609	Other Residential Care Services	Yes
	8710	Child Care Services	Yes
	8790	Other Social Assistance Services	Yes
Water services	2811	Water Supply	Yes
	2812	Sewerage and Drainage Services	Yes
Communications	5610	Radio Broadcasting	Yes
	5621	Free-to-Air Television Broadcasting	Yes
	5622	Cable and Other Subscription Broadcasting	No
	5700	Internet Publishing and Broadcasting	Yes
	5910	Internet Service Providers and Web Search Portals	Yes
	5921	Data Processing and Web Hosting Services	Yes
	5922	Electronic Information Storage Services	Yes
	5801	Wired Telecommunications Network Operation	Yes
	5802	Other Telecommunications Network Operation	Yes

	5809	Other Telecommunications Services	Yes
	600	Coal Mining	Yes
	700	Oil and Gas Extraction	Yes
	1701	Petroleum Refining and Petroleum Fuel Manufacturing	Yes
	1709	Other Petroleum and Coal Product Manufacturing	Yes
	2611	Fossil Fuel Electricity Generation	Yes
Energy	2612	Hydro-Electricity Generation	Yes
	2619	Other Electricity Generation	Yes
	2620	Electricity Transmission	Yes
	2630	Electricity Distribution	Yes
	2640	On Selling Electricity and Electricity Market Operation	Yes
	2700	Gas Supply	Yes
	4610	Road Freight Transport	Yes
	4621	Interurban and Rural Bus Transport	No
	4622	Urban Bus Transport (Including Tramway)	No
	4623	Taxi and Other Road Transport	No
	4710	Rail Freight Transport	Yes
	4720	Rail Passenger Transport	No
	4810	Water Freight Transport	Yes
	4820	Water Passenger Transport	No
	5010	Scenic and Sightseeing Transport	No
	5021	Pipeline Transport	Yes
	5029	Other Transport n.e.c.	Yes
	4900	Air and Space Transport	Yes
	5211	Stevedoring Services	Yes
	5212	Port and Water Transport Terminal Operations	Yes
	5219	Other Water Transport Support Services	Yes
Logistics	5220	Airport Operations and Other Air Transport Support Services	Yes
	5291	Customs Agency Services	Yes
	5292	Freight Forwarding Services	Yes
	5299	Other Transport Support Services n.e.c.	Yes
	5301	Grain Storage Services	Yes
	5309	Other Warehousing and Storage Services	Yes
	3311	Wool Wholesaling	No
	3312	Cereal Grain Wholesaling	No
	3319	Other Agricultural Product Wholesaling	No
	3321	Petroleum Product Wholesaling	Yes
	3322	Metal and Mineral Wholesaling	No
	3323	Industrial and Agricultural Chemical Product Wholesaling	Yes
	3331	Timber Wholesaling	No
	3332	Plumbing Goods Wholesaling	No
	3339	Other Hardware Goods Wholesaling	No

3411	Agricultural and Construction Machinery Wholesaling	No
3419	Other Specialised Industrial Machinery and Equipment Wholesaling	No
3491	Professional and Scientific Goods Wholesaling	No
3492	Computer and Computer Peripheral Wholesaling	No
3493	Telecommunication Goods Wholesaling	Yes
3494	Other Electrical and Electronic Goods Wholesaling	No
3499	Other Machinery and Equipment Wholesaling n.e.c.	No
3501	Car Wholesaling	No
3502	Commercial Vehicle Wholesaling	Yes
3503	Trailer and Other Motor Vehicle Wholesaling	Yes
3504	Motor Vehicle New Parts Wholesaling	Yes
3505	Motor Vehicle Dismantling and Used Parts Wholesaling	Yes
3601	General Line Grocery Wholesaling	No
3602	Meat, Poultry and Smallgoods Wholesaling	No
3603	Dairy Produce Wholesaling	No
3604	Fish and Seafood Wholesaling	No
3605	Fruit and Vegetable Wholesaling	No
3606	Liquor and Tobacco Product Wholesaling	No
3609	Other Grocery Wholesaling	No
3711	Textile Product Wholesaling	Yes
3712	Clothing and Footwear Wholesaling	No
3720	Pharmaceutical and Toiletry Goods Wholesaling	Yes
3731	Furniture and Floor Covering Wholesaling	No
3732	Jewellery and Watch Wholesaling	No
3733	Kitchen and Diningware Wholesaling	No
3734	Toy and Sporting Goods Wholesaling	No
3735	Book and Magazine Wholesaling	No
3736	Paper Product Wholesaling	No
3739	Other Goods Wholesaling n.e.c.	No
3800	Commission-Based Wholesaling	No
3911	Car Retailing	No
3912	Motor Cycle Retailing	No
3913	Trailer and Other Motor Vehicle Retailing	No
3921	Motor Vehicle Parts Retailing	No
3922	Tyre Retailing	No
4000	Fuel Retailing	Yes
4110	Supermarket and Grocery Stores	No
4121	Fresh Meat, Fish and Poultry Retailing	No
4122	Fruit and Vegetable Retailing	No
4123	Liquor Retailing	No
4129	Other Specialised Food Retailing	No
4211	Furniture Retailing	No
4212	Floor Coverings Retailing	No

	4213	Houseware Retailing	No
	4214	Manchester and Other Textile Goods Retailing	No
	4221	Electrical, Electronic and Gas Appliance Retailing	No
	4222	Computer and Computer Peripheral Retailing	No
	4229	Other Electrical and Electronic Goods Retailing	No
	4231	Hardware and Building Supplies Retailing	No
	4232	Garden Supplies Retailing	No
	4241	Sport and Camping Equipment Retailing	No
	4242	Entertainment Media Retailing	No
	4243	Toy and Game Retailing	No
	4244	Newspaper and Book Retailing	No
	4245	Marine Equipment Retailing	No
	4251	Clothing Retailing	No
	4252	Footwear Retailing	No
	4253	Watch and Jewellery Retailing	No
	4259	Other Personal Accessory Retailing	No
	4260	Department Stores	No
	4271	Pharmaceutical, Cosmetic and Toiletry Goods Retailing	Yes
	4272	Stationery Goods Retailing	No
	4273	Antique and Used Goods Retailing	No
	4274	Flower Retailing	No
	4279	Other Store-Based Retailing n.e.c.	No
	4310	Non-Store Retailing	No
	4320	Retail Commission-Based Buying and/or Selling	No
	7510	Central Government Administration	Yes
	7520	State Government Administration	Yes
	7530	Local Government Administration	Yes
	7540	Justice	Yes
	7551	Domestic Government Representation	Yes
	7552	Foreign Government Representation	Yes
Government	7720	Regulatory Services	Yes
	7600	Defence	Yes
	7711	Police Services	Yes
	7712	Investigation and Security Services	Yes
	7713	Fire Protection and Other Emergency Services	Yes
	7714	Correctional and Detention Services	Yes
	7719	Other Public Order and Safety Services	Yes

Appendix B: Stationarity and Cointegration tests

This appendix presents the results for the citric acid price and quantity variables in quarterly form; results for the other chemicals yielded similar results.

Table B.1 – Results from Augmented Dickey-Fuller test on key variables[a]

Variable	ADF statistic	Stationary or non-stationary
Log weighted average price	-2.52	Non-stationary
Weighted average price	-2.87	Non-stationary
Log difference of weighted average price	-4.98	Stationary
Log quantity	-2.86	Non-stationary
Quantity	-2.94	Non-stationary
Log difference of quantity	-8.82	Stationary

a. Stationary or non-stationary results are reported at the 5 per cent significance level.

Source: ABS (*Merchandise Imports and Import Clearances*, 2010-2019, unpublished).

To test for cointegration, the Engle-Granger two-step method was chosen due to the small sample size. The Engle-Granger two-step method creates residuals based on the static regression and then tests the residuals for the presence of unit-roots (non-stationarity). It then tests for the stationarity of the residuals. If the time series is cointegrated, the Engle-Granger method will show the residuals to be stationary.[8]

Quarterly log quantity is regressed on log price, and quarterly log quantity is regressed on log price and log food expenditure. The residuals are then tested for stationarity.

$$\ln(q_t) = \beta_0 + \beta_1 \ln(p_t) + \varepsilon_t \qquad (A)$$

$$\ln(q_t) = \beta_0 + \beta_1 \ln(p_t) + \beta_2 \ln(m_t) + \varepsilon_t \qquad (B)$$

[8] The limitation of the Engle-Granger method is that if there are more than two variables, the method may show more than two cointegrating relationships. Another limitation is that it is a single equation model. However, some of the drawbacks have been addressed in recent cointegration tests such as the Johansen and Phillips-Ouliaris tests.

The Johansen test is used to test cointegrating relationships between several non-stationary time series data. Compared to the Engle-Granger test, the Johansen test allows for more than one cointegrating relationship. However, it is subject to asymptotic properties (large sample size) since a small sample size would produce unreliable results. The Johansen test was also applied, to verify the Engle-Granger results.

The Phillips-Ouliaris tests consists four distinct tests. Two are similar to the Engle-Granger test, only using a Phillips & Perron-like approach replaces the lags in the ADF test with a long-run variance estimator. The other two use variance-ratio like approaches to test. In both cases the test stabilizes when there is no cointegration and diverges due to singularity of the covariance matrix of the I(1) time series when there is cointegration.

The Augmented Dickey-Fuller test showed that equations A and B were cointegrated based on the AIC number of lags (1) (table 4). For lags greater than one, cointegration did not exist.

As a robustness test, the Johansen test was also performed and it found that there was evidence of at least one cointegrating relationship for log quantity and log price, and for log quantity, log price and log food expenditure.

Table 4 – Results from the Engle-Granger two-step method[a]

Specification	ADF test statistic	Critical value	Conclusion
Equation A	-5.8	-3.5	Reject the null and conclude cointegration
Equation B	-5.3	-3.5	Reject the null and conclude cointegration

a. Critical values are reported for the 5 per cent level of significance.

Appendix C: Other regression results for chemicals

C.1 Results for Citric Acid (data aggregated into quarters)

In this section, we run the ARDL equations described in Table 4 with quarterly data instead of monthly. Sales are averaged over quarters rather than months, and the weighted average price in each quarter is constructed. Dummies are quarterly instead of monthly.

Using quarterly data allows us to use the activity variable (food expenditure) without interpolation. Using quarterly data can also smooth the impact of a shipment that is an outlier; but it also greatly reduces the number of observations.

Table C.1 – ARDL model results for Citric Acid[a]

Variable	Specification 1	Specification 2	Specification 3	Specification 4
P_t	-0.37 (0.52)	0.09 (0.49)	-0.64 (0.53)	-0.34 (0.74)
M_t		-0.76 (8.58)		-24.30 (20.24)
Q_{t-1}	0.19 (0.17)	-0.12 (0.18)	0.10 (0.17)	-0.13 (0.23)
Q_{t-2}			0.23 (0.17)	-0.09 (0.30)
Q_{t-3}			0.37 (0.19)	-0.13 (0.28)
P_{t-1}	0.46 (0.52)	0.25 (0.47)	0.13 (0.51)	0.27 (0.54)
M_{t-1}		1.00 (8.61)		61.62 (25.56)
N	**39**	**36**	**37**	**34**
R-squared	**0.17**	**0.35**	**0.22**	**0.23**

a. Data ranged from 2010 to 2019. The optimal lags for food expenditure were estimated to be 8, but given this was too high, 3 was used instead. The specifications that include food expenditure had less observations because data were only available up to the 1st quarter of 2019. Standard errors presented in parentheses. *** p<.01 ** p<.05 * p<.1

Sources: ABS (*Merchandise Imports and Import Clearances*, 2010-2019, unpublished); ABS (*Australian National Accounts: National Income, Expenditure and Product*, December 2022, Cat. no. 5206.0, table 8).

None of the coefficients are significantly different from zero (and the coefficient on the activity variable and its lags is improbably large in Specification 4). This is most likely due to the small number of observations.

The ECM was also estimated with quarterly data, which allows us to estimate four different specifications:

- Specification 1 – equation 2 with only β_1, β_3 and β_4
- Specification 2 – equation 2 with only β_1, β_3, β_4 and γ_t
- Specification 3 – equation 2 with only β_1, β_2 , β_3, β_4 and β_5
- Specification 4 – equation 2.

In all of these specifications, the lag length is restricted to 1, given the limited number of degrees of freedom. Again, significance was a challenge, given the small number of observations.

Table C.2 – ECM results for citric acid[a]

Coefficient	Specification 1	Specification 2	Specification 3	Specification 4
$\Delta logP_t$	-0.93* (0.52)	-0.37 (0.52)	-0.70 (0.52)	-0.09 (0.49)
$\Delta \log M_t$			4.99 (9.56)	0.76 (8.58)
$logP_{t-1}$	-0.02 (0.50)	-0.09 (0.47)	-0.08 (0.49)	-0.16 (0.45)
$logq_{t-1}$	-0.83*** (0.16)	-0.81*** (0.17)	-1.06*** (0.17)	-1.12*** (0.18)
$logM_{t-1}$			1.80*** (0.65)	1.76 (0.58)
N	**39**	**39**	**36**	**36**
R-squared	**0.46**	**0.54**	**0.57**	**0.66**

a. Data ranged from 2010 to 2019. The regressions that include food expenditure had less observations as data were only available up to the 1st quarter of 2019. Standard errors presented in parentheses. *** p<.01 ** p<.05 * p<.1

C.2 Results for Disodium carbonate, glycine, melamine with quarterly data

Autoregressive distributed lags model (ARDL)

The following ARDL equation (for log variables) is used to estimate demand elasticity for each vulnerable chemical in quarter t.

$$Q_t = \beta_0 + \beta_1 P_t + \beta_2 M_t + \sum_{i=1}^{p} \delta_i Q_{t-i} + \sum_{i=1}^{q} \gamma_i P_{t-i} + \sum_{i=1}^{z} \pi_i M_{t-i} + \gamma_t + \epsilon_t \qquad (1)$$

Where:

- Q_t *is* quantity demanded at time t
- β_0 is the constant
- β_1 is the **coefficient of interest** and shows the short-run price elasticity of demand, which measures the percentage change in quantity demanded resulting from a 1 per cent change in price
- β_2 controls for current levels of the activity variable (log of GDP per capita)
- δ_i are the autoregressive lags for the log quantity of a chemical imported at time period t-i
- γ_i are the lagged coefficients for log price at time t-i
- π_i are the lagged coefficients for the log activity variable at time t-i
- γ_t includes dummy variables for quarters
- ϵ_t is the error term.

ARDL results with outliers

The following model specifications were estimated in Table C.3[9]:

- Specification 1 – equation 1 with a lag length of one without the activity variable (M_t)
- Specification 2 – equation 1 with a lag length of one with the activity variable
- Specification 3 – equation 1 with optimal AIC lag length for each variable without the activity variable[10]
- Specification 4 – equation 1 with optimal AIC lag length for each variable with the activity variable.

[9] Melamine had a small sample size at the transaction-level (339). For Disodium carbonate, specification 4 and 5 showed evidence of autocorrelation. For melamine, specification 1, 3 and 5 showed evidence of autocorrelation.

[10] AIC lag lengths were restricted to a maximum length of three to help improve the degrees of freedom in the model. For example, if the AIC lag length was estimated to be 6, only 3 lags was used in the model.

Table C.3 – ARDL model for disodium carbonate, melamine, and glycine[a]

Variable	Specification 1	Specification 2	Specification 3	Specification 4
Disodium Carbonate				
P_t	-2.27 (1.34)	-4.11** (1.41)	-2.79** (1.25)	-2.70* (1.56)
N	**39**	**36**	**38**	**34**
R-squared	**0.15**	**0.39**	**0.48**	**0.46**
Melamine				
P_t	1.15** (0.47)	1.35** (0.41)	0.55 (0.44)	0.88** (0.40)
N	**35**	**35**	**33**	**32**
R-squared	**0.50**	**0.55**	**0.39**	**0.53**
Glycine derivatives				
P_t	1.57 (1.28)	0.78 (1.40)	-0.91 (0.70)	-0.92 (0.83)
N	**31**	**28**	**32**	**26**
R-squared	**0.31**	**0.14**	**0.23**	**0.06**

a. Data ranged from 2010 to 2019 (some chemicals had less data than others). The regressions that include GDP per capita had less observations as data were only available up to the 1st quarter of 2019. Standard errors presented in parentheses. *** p<.01 ** p<.05 * p<.1

Sources: ABS (*Merchandise Imports and Import Clearances*, 2010-2019, unpublished); ABS (*Australian National Accounts: National Income, Expenditure and Product*, December 2022, Cat. no. 5206.0, table 1).

Error correction model (ECM)

The following ECM is used to estimate the demand elasticity for each vulnerable chemical.[11] The dependent variable is the log difference of quantity demanded at time t.

$$\Delta log q_t = \beta_0 + \beta_1 \, \Delta log P_t + \beta_2 \Delta log M_t + \beta_3 log P_{t-i} + \beta_4 log q_{t-i} + \beta_5 log M_{t-i} + \gamma_t + \varepsilon_t \qquad (2)$$

Where:

- β_0 is the constant
- β_1 **is the coefficient of interest** and shows the short-run price elasticity of demand, which measures the percentage change in quantity demanded resulting from a 1 per cent change in price in the short run

[11] Log price and log quantity were stationary and cointegrated for each chemical.

- β_2 controls for short-run changes in the activity variable (log of food expenditure, GDP or GDP per capita)
- β_3 , β_4 and β_5 are the lagged coefficients for log price, log quantity and log activity variable at time t-i. This controls for the long-run equilibrium
- γ_t includes dummy variables for quarters
- ϵ_t is the error term.

The following model specifications – with a lag length of 1 - are included in Table C.3[12]:

- Specification 1 – equation 2 with only β_1, β_3 and β_4
- Specification 2 – equation 2 with only β_1, β_3, β_4 and γ_t

Table C.4 – ECM results for vulnerable chemicals[a]

Coefficient	Specification 1	Specification 2
Disodium Carbonate		
$\Delta log P_t$	-2.75** (1.27)	-2.75** (1.14)
$log q_{t-1}$	-0.68*** (0.18)	-1.69*** (0.19)
N	**39**	**39**
R-squared	**0.51**	**0.77**
Melamine		
$\Delta log P_t$	0.63 (0.61)	1.00 (0.66)
$log q_{t-1}$	-1.01*** (0.22)	-0.86*** (0.26)
N	**35**	**35**
R-squared	**0.39**	**0.69**
Glycine derivatives		
$\Delta log P_t$	1.86 (1.48)	2.71 (1.83)
$log q_{t-1}$	-0.77*** (0.20)	-0.90*** (0.30)
N	**31**	**31**
R-squared	**0.43**	**0.59**

a Data ranged from 2010 to 2019 (some chemicals had less data than others). The regressions that include GDP per capita had less observations as data were only available up to the 1st quarter of 2019. Standard errors presented in parentheses. *** p<.01 ** p<.05 * p<.1

[12] All regressions showed no evidence of autocorrelation.

No specifications with the activity variable were run, as log GDP per capita was a stationary variable for each vulnerable chemical.

The results broadly confirm the results in *Vulnerable Supply Chains* (2021). It was only possible to reject the hypothesis of a zero price elasticity for disodium carbonate. Further research into glycine and melamine is therefore warranted.

C.3 Other (non-vulnerable) chemicals with high volume data

To estimate demand elasticity, it is important to have many observations to improve the robustness of the results. Chemicals with 'high volume' data included calcium chloride and magnesium sulphate. Chemicals were defined as high-volume if they had at least 10 observations in each quarter, and at least nine years of quarterly data. These chemicals were used to estimate the ARDL and ECM models at a monthly level.

ARDL monthly results with outliers[13]

Table C.5 – ARDL monthly model for high-volume chemicals[a]

Variable	Specification 1	Specification 2	Specification 3	Specification 4
Calcium chloride				
P_t	-0.75*** (0.11)	-0.81*** (0.11)	-0.76*** (0.11)	-0.80*** (0.11)
N	**119**	**109**	**118**	**107**
R-squared	**0.48**	**0.52**	**0.47**	**0.54**
Magnesium sulphate				
P_t	-0.78** (0.29)	-0.90*** (0.30)	-0.85*** (0.31)	-0.85*** (0.31)
N	**119**	**109**	**118**	**107**
R-squared	**0.31**	**0.41**	**0.35**	**0.41**

a. Data ranged from 2010 to 2019 (some chemicals had less data than others). The regressions that include GDP per capita had less observations as data were only available up to the 1st quarter of 2019. Standard errors presented in parentheses. *** p<.01 ** p<.05 * p<.1

Sources: ABS (*Merchandise Imports and Import Clearances*, 2010-2019, unpublished); ABS (*Australian National Accounts: National Income, Expenditure and Product*, December 2022, Cat. no. 5206.0, table 1).

13 Specification 1 had evidence of autocorrelation at the 95 per cent confidence interval for both Calcium Chloride and Magnesium sulphate.

ECM monthly results

Variables for calcium chloride and magnesium sulphate at the monthly level were stationary, and therefore, an ECM should not be estimated. However, the results are still included for comparison.

Table C.7 – Monthly ECM results for high-volume chemicals[a]

Coefficient	Specification 1	Specification 2
Calcium chloride		
$\Delta log P_t$	-0.81*** (0.10)	-0.75*** (0.11)
$log q_{t-1}$	-0.60*** (0.09)	-0.64*** (0.09)
N	**119**	**119**
R-squared	**0.54**	**0.58**
Magnesium sulphate		
$\Delta log P_t$	-0.73** (0.29)	-0.78** (0.30)
$log q_{t-1}$	-0.47** (0.08)	-0.51*** (0.09)
N	**119**	**119**
R-squared	**0.32**	**0.47**

a. Data ranged from 2010 to 2019 (some chemicals had less data than others). Standard errors presented in parentheses. *** p<.01 ** p<.05 * p<.1

Source: Commission estimates based on ABS (*Merchandise Imports and Import Clearances*, 2010-2019, unpublished).

Appendix D: Background to BLADE

What is BLADE?

BLADE is a 'collection of integrated, linked longitudinal datasets' of Australian businesses (Hansell and Rafi 2018, p. 133). It provides a framework for linking ABS business surveys with administrative data on business via an Australian Business Number (ABN). This makes BLADE the most comprehensive database on firms in Australia.

BLADE combines tax, trade, and intellectual property business data with ABS data to provide a better understanding of the Australian economy and business performance over time. It is constructed with partnerships between many government departments.

Available data (July 2020 release)

A summary of the data available in BLADE as at July 2020 is presented in figure 1.3. Revisions of BLADE data are released annually. The main administrative data come from the ATO, forming the BLADE 'core'. These data include business income and taxation data. More recently, administrative data on intellectual property (from IP Australia) and merchandise trade (from DHA, ie Customs) have also been linked to BLADE.

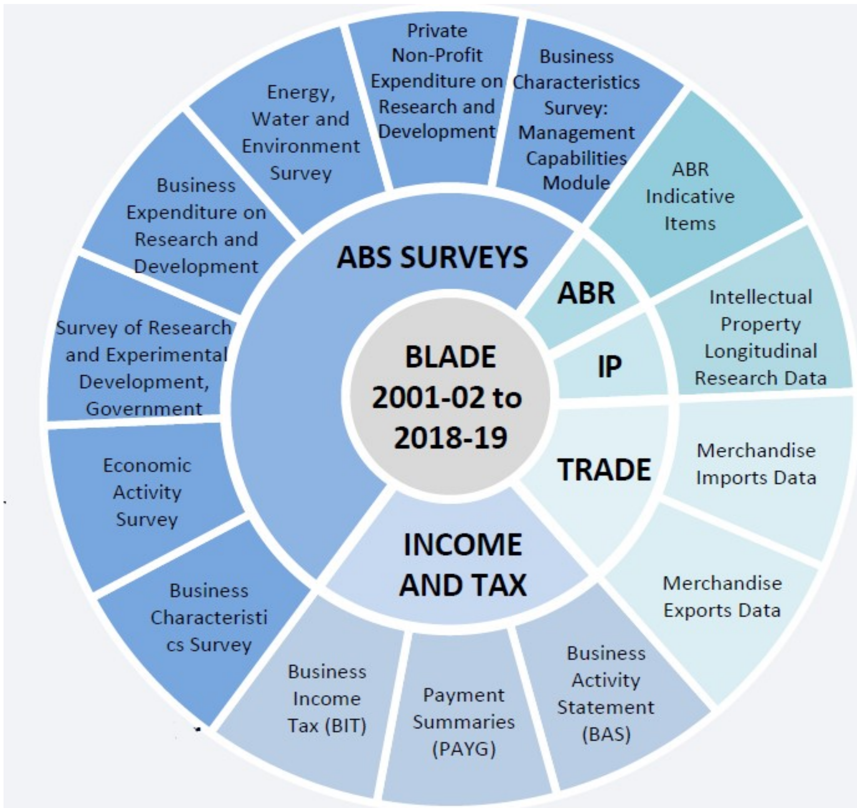
The ABS survey data includes, for example, the Economic Activity Survey, Business Characteristics Survey, Survey of R&D, and Energy Water Environment Survey. Any ABS business survey that uses the ABS common survey frame can, in theory, be integrated in BLADE.

Administrative data are longitudinal, with most administrative datasets covering the period 2001-02 to 2018-19, but most of the survey data are cross-sectional and relate to selected years and selected firms.

Merchandise trade data

Administrative merchandise trade data are available for 2003-04 to 2018-19. These data are sourced from customs declarations and collected by the DHA. The data is limited to transactions of goods only (that is, it excludes services). The data for imports and exports by firms (captured by ABNs) includes information such as the commodity type (10-digit HTISC), country of destination/departure, and value.

Figure 5 **What is covered in BLADE?[a]**



[a] ABR = Australian Business Register is the whole-of-government register of businesses and is maintained by the ATO. It contains information on ABNs and related business information (location, business structure, industry, etc.).

Source: ABS (BLADE Data Availability and Access, User information pack, June 2020)

Coverage and scope

The July 2020 release of BLADE contains data on all active businesses from 2001-02 to 2018-19. There are two populations in the data:

- non-profiled population, which are businesses with simple structures such that one ABN equates to one business. This covers the vast majority of businesses in BLADE
- profiled population, which are large, complex and diverse groups of businesses that are organised under Enterprise Groups (usually major and well-known companies, often with operations spread across industry divisions). The profiled population accounts for a small per cent of all ABN units, but a large per cent of output (Hansell and Rafi 2018, p. 134).

The number of firms (sample size) is dependent on which dataset is being used within BLADE. Administrative data have the broadest coverage, for example, in 2014–15 there were just under 2.4 million business income tax records (Hansell and Rafi 2018, p. 136). The coverage of the survey data depends on the scope of the survey. For example, in 2016-17 the Business Characteristics Survey sampled around 7,600 businesses (ABS source).