How do consumers react to the price of food? Evidence from supermarket micro data

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Author Note

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Abstract

How consumers react to the price of food is a question of substantial economic and health policy importance. Food makes up a substantial share of household's overall budget, and choices between different food stuffs can have important economic and health outcomes. But analysing the impact of food prices is difficult as they evolve more rapidly than the measurement of economic statistics, and measurement of the volume of household consumption is less frequent than price measurement. This paper draws on statistics the ABS has generated from supermarket scanner data, which provides information on both the price and volume of sales of millions of individual items. Using this data, the paper analyses the way that consumers are responding to price changes of a range of goods. The economic and health implications of these responses are considered, showing how the impact of price changes differs across different categories of consumption.

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Introduction

In the 2021-22 financial year Australian households spent $118.5 billion on food (in current price terms), or a little over 10 per cent of total household consumption.[1] But prior to recent years little real time data has been available on this sector. The Australian Bureau of Statistics (ABS) has historically used a mix of intermittent household[2] and product surveys[3], quarterly price measurement and monthly retail trade measurement to produce estimates of food consumption. In practice this has meant that it wasn't possible to measure changes in the composition of food consumption over time, or consumer responses to prices.

There are many questions where it would be useful to have frequent detail on the composition of food expenditure. It is useful for economists and policy makers to understand how consumers react to price changes, shocks such as the COVID-19 pandemic, or the introduction of new policies on health labelling. It would also allow for more accurate measurement of the impact of price changes on households, by allowing the consumption basket to change.

The introduction of new data sources has allowed the ABS to improve the way that it produces statistics on food consumption, and to offer new insights on the way that consumers behave.

This paper discusses three areas where the ABS has made use of scanner data – the Consumer Price Index (CPI), National Accounts Household Final Consumption Expenditure on

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[1] Australian National Accounts: National Income, Expenditure and Product, December 2022 | Australian Bureau of Statistics (abs.gov.au). Note this includes consumption of non-alcoholic beverages.

[2] Household Expenditure Survey, Australia: Summary of Results, 2015-16 financial year | Australian Bureau of Statistics (abs.gov.au)

[3] 8622.0 - Retail and Wholesale Industries, Australia, 2012-13 (abs.gov.au)

Food (HFCE), and Apparent Consumption of Foodstuffs (ACFS). The paper outlines how the key methods have been updated to reflect the use of scanner data and shows some of the insights that can be derived using this more detailed information. The paper also shows how the introduction of new methods to account for changes to consumption baskets has overcome past measurement issues in the CPI. The paper concludes by noting some of the limitations of the analysis, and potential future work.

About the supermarket data set

The ABS currently receives scanner data from major supermarket chains, this data accounts for approximately 84% of all expenditure by consumers through supermarkets. The datasets are supplied weekly with the following dimensions:

- Product/item description
- Quantity of items sold
- Dollar value of items sold
- Geographical location of stores

Price insights from Scanner data

Prior to the availability of scanner data to measure the CPI, prices were collected either monthly or quarterly for a sample of products in a range of stores across the eight capital cities. In the case of supermarkets, ABS price collectors would visit a small number of stores each month and collect prices for a fraction of all the items available. This approach limited the coverage of price collection in three areas: geography – the location and number of the stores were small; time – point in time pricing of once per month was used; and products – a few hundred products would be priced from the tens of thousands of available products.

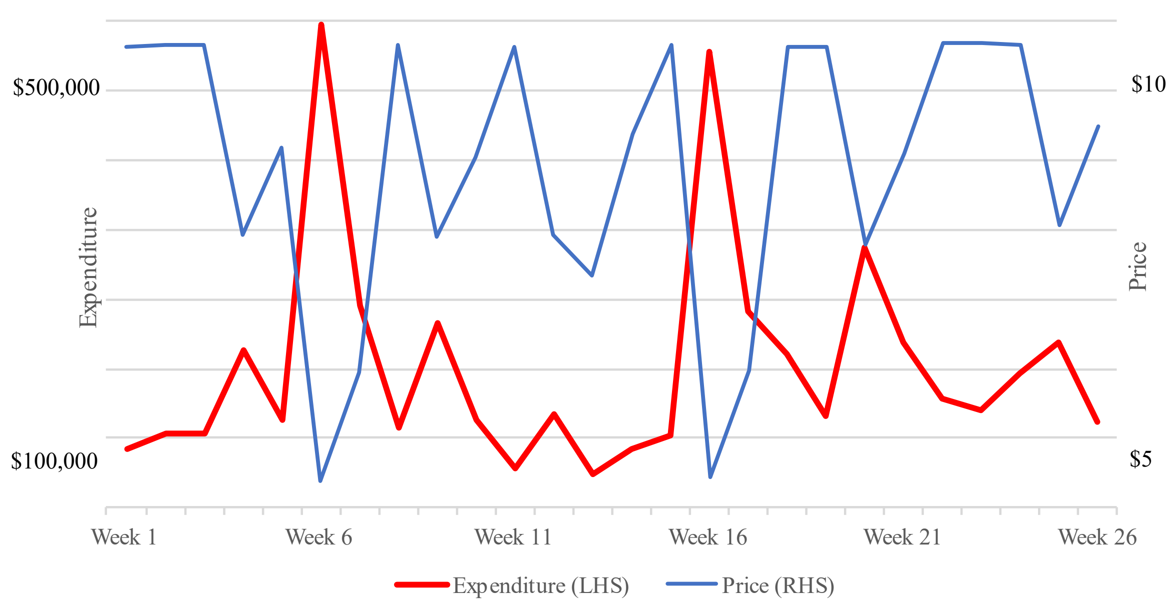
Scanner data on the other hand, collected via barcode technology whenever an item is purchased at a retailer, possesses the following characteristics:

- A census rather than a sample of products, with hundreds of thousands of products priced.
- Every store included for those supermarkets providing the scanner data, providing greater geographic detail.
- High frequency data collection with weekly information.
- Datasets include expenditure data in addition to pricing data.

One thing that was evident in the scanner data was how responsive consumers are to discounting - everyone loves a good special. When a product is discounted consumers purchase far more than usual, causing total expenditure on that item to rise well above its normal level. Then, when the product returns to its normal price, expenditure levels drop dramatically as few consumers have any need to buy at the higher price level – they made sure their pantries were nicely stocked while the product was discounted. Chart 1 illustrates a typical relationship between expenditure and price. Note how expenditure responds strongly to sharp price discounts.

This example is typical of any non-perishable item that can be stored at home for a number of weeks or months.

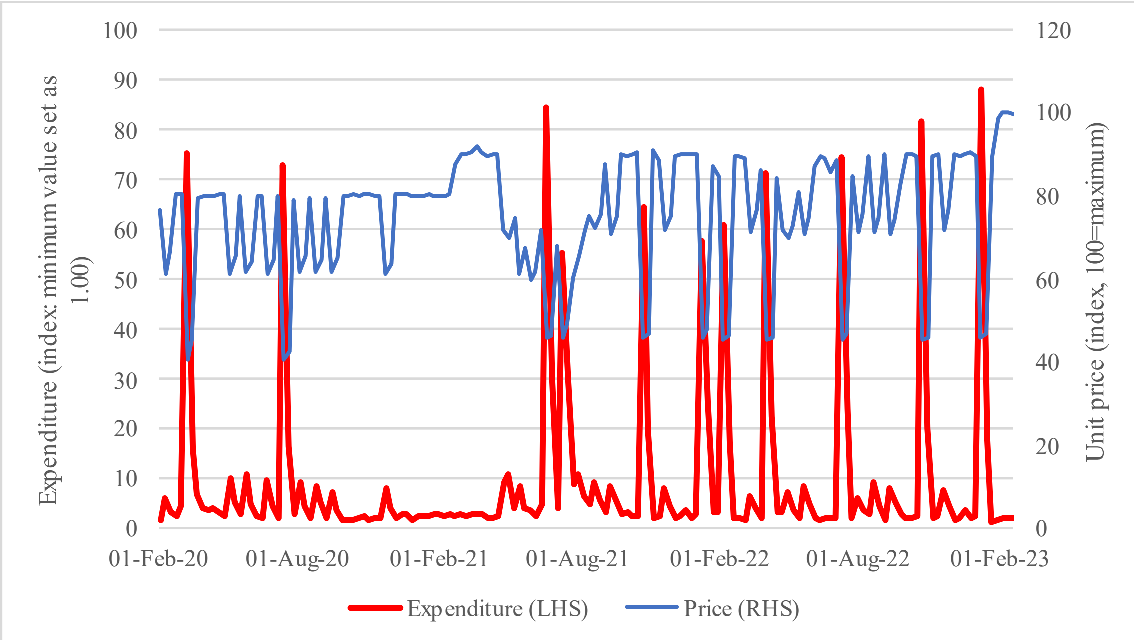
Chart 1: Typical relationship between price and expenditure



Source: Scanner data example for an individual product

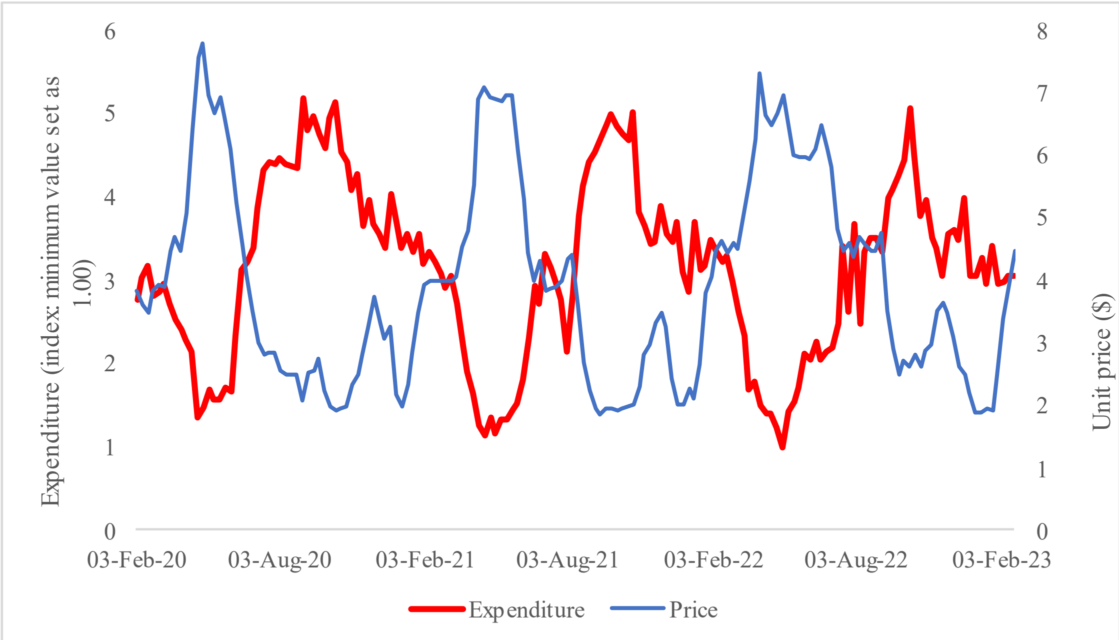
An example of this can be seen for a premium brand of olive oil (Chart 2). When the price is normal, very little is purchased. When the price is discounted, expenditure increases by many, many factors from its typical level.

Chart 2: Olive Oil expenditure and price



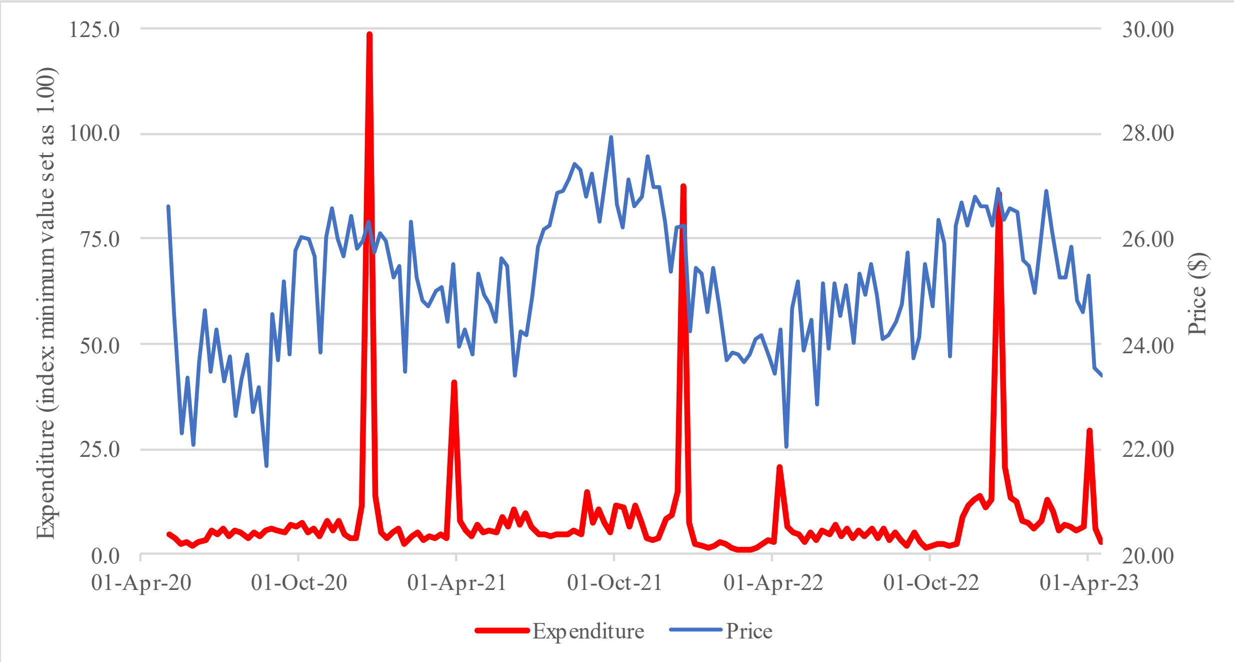
This phenomenon also occurs for fruit and vegetables, however prices are discounted for a different reason: when the fruit or vegetable is in season and supply is plentiful, prices fall (Chart 3). This sees expenditure rise considerably for the in-season products.

Chart 3: Berries price and expenditure



The scanner data also shows how consumers respond around events such as Christmas and Easter. The following Chart 4 shows how expenditure on prawns increases dramatically around Christmas and Easter regardless of the prevailing price.

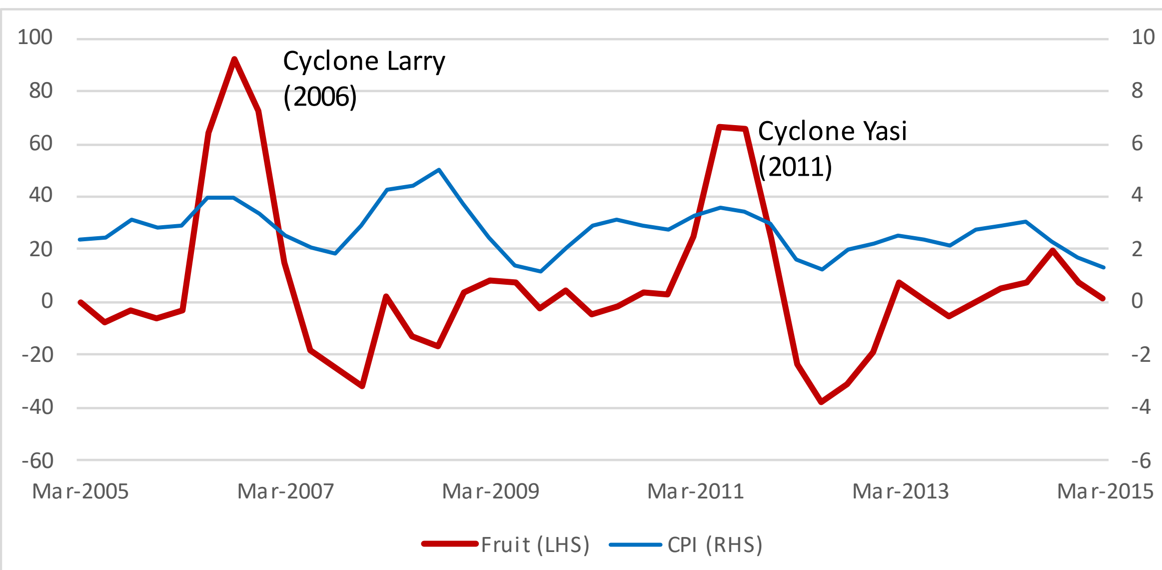
Chart 4: Prawn price and expenditure



Cyclones & Banana

A well-known example of where product substitution bias occurred in 2006 was when Cyclone Larry swept through North Queensland, devastating approximately 80% of Australia's banana crops. This sudden and extensive supply disruption resulted in banana prices rising by as much as 400%. At that point in time, the fruit expenditure class of the Australian CPI was constructed using the bilateral Laspeyres index method, meaning that weights were fixed to a point set in the past. A dramatic price rise, as was seen for bananas, typically causes consumers to seek cheaper alternatives. This means that in real life the expenditure on bananas fell, however this shift in expenditure was unable to be captured in the CPI with the absence of scanner data. The inability to update weights to reflect current expenditure meant that the CPI recorded dramatic spikes during this period, as shown in Figure X. At the same time as the impact of the 400% price rise in bananas, the CPI annual movement rose from 3% to 4%. There was a similar occurrence in 2011 with Cyclone Yasi destroying a large share of banana crops.

Chart 9: Fruit and the impact of tropical cyclone Larry



Consumers substitute products under less dramatic circumstances too – for example, they will buy more stone fruit in summer when it's cheap and in-season but seek cheaper alternatives in winter when it's out of season and hence more expensive. Scanner data captures both the one-off shocks like we saw with the cyclone impact on bananas, but also the seasonal nature of expenditure on fruit and vegetables as well as other changing expenditure patterns around periods such as Christmas and Easter. .

Introducing multilateral methods using scanner data in CPI compilation

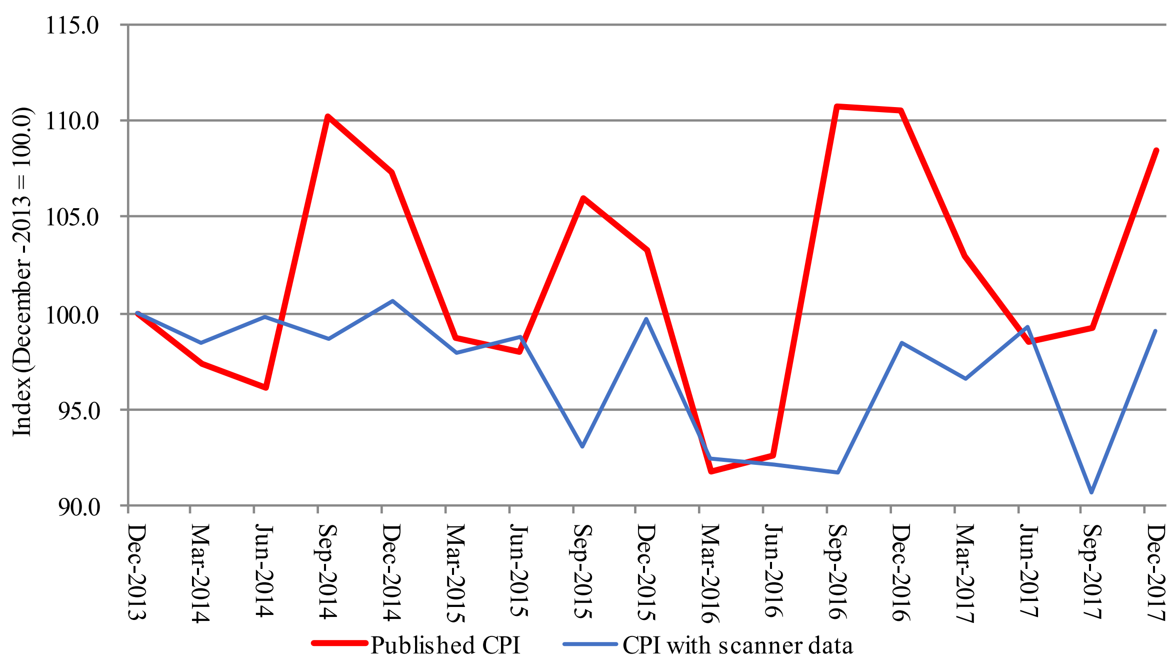
Scanner data contains two key variables - revenue and quantity. Average prices are derived by dividing the revenue for a product by the quantity sold. Access to revenue data opens a world of opportunity, as it can be used to calculate expenditure shares, or in other words, it provides timely weighting information. Revenue data is extremely valuable in measuring price change as it enables the CPI to dynamically weight the items based on timely expenditure data at a very detailed level. To do this, the ABS makes use of relatively new and highly sophisticated methods, known as 'multilateral methods', which maximise the use of the scanner data. The ABS's extensive use of scanner data to measure the CPI is world leading and is considered international best practice to incorporating big data into official statistics.

To revisit our earlier example, how would multilateral indexes have prevented product substitution from distorting the CPI back in 2006? The expenditure data would have captured substitution by consumers, meaning that fewer people buying bananas because of the price rises would result in bananas having a lower weight. So overall, the impact of bananas on the CPI would have been greatly reduced, avoiding the large spikes that we saw under the methods used at the time.

Unfortunately we don't have access to scanner data from the periods the cyclones impacted banana prices, however we are able to analyse more recent years for the Fruit expenditure class.

Figure 10. shows the volatility of the fruit expenditure class under traditional price collection with the traditional fixed weight method, compared to the same series recreated with scanner data. The large peaks and troughs under the traditional approach are due to weights being held fixed regardless of quantities purchased, meaning that out of season fruits have a significant impact on the index even if a small volume is purchased in a given quarter.

Chart 10: Fruit price index comparing methods



Insights into Apparent Consumption of Food

Household Final Consumption Expenditure on Food[4]

Household Final Consumption Expenditure (HFCE) is a major component of Gross Domestic Product on an Expenditure basis in the National Accounts, making up 50% of GDP. Food is in turn a significant component of HFCE (around 10.5% of HFCE).

Prior to the introduction of the scanner data based method, apparent consumption of Food was estimated using an indicator approach.[5] Current price expenditure on food was estimated using information from the monthly Retail Business Survey, with weights from the irregular Retail and Wholesale Industries Survey used to convert from turnover by industry to turnover by product category.

From the September quarter 2022 release, the Food component of HFCE has been estimated using scanner data. The steps involved are:

- Removal of outliers and anomalies

  The scanner data is a by-product of the point of sale systems of the supermarkets, and therefore can contain outliers and anomalies that need to be removed for statistical purposes. This step also involves imputing missing values.

- Mapping to the HFCE classification

  The scanner data contains in aggregate around 2 million individual stock keeping unit products, including both food and non-food products. To allow for inclusion in the National Accounts this needs to be converted to a classification used in the

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[4] This section is adapted from Using scanner data to estimate household consumption, September 2021 | Australian Bureau of Statistics (abs.gov.au), which contains greater detail.

[5] Sources and methods - Quarterly | Australian Bureau of Statistics (abs.gov.au)

National Accounts. In this case the Input Output Product Classification (IOPC) is used. This conversion is done using an Intelligent Coder[6], a machine learning tool for working with large-scale databases.

- Adjusting for missing scope and coverage

  The supermarket scanner data contains around 60-65% of total food consumption included in the National Accounts. Adjustments are made using other data sources to account for the food expenditure in these other outlets – for instance, other supermarkets, fruit & vegetable retailers and so on.

- Price and volume estimations

  For each IOPC category a price index is estimated using the established CPI methods for measuring prices from the scanner data. This also allows for estimates of the volume of consumption.

Further detail can be found in the September 2021 methodology paper.

The final output of this process is an estimate for consumption of food at three levels:

- Total Food consumption
- Food consumption on a Supply Use Product Classification basis (13 categories)
- Food consumption on an Input Output Product Classification basis (69 categories)

For each category the current price and chain volume measure is published in a data cube with each quarterly release of the National Accounts. Total Food consumption is also published for each State and Territory in other tables of the National Accounts.

[6] 1504.0 - Methodological News, Sep 2017 (abs.gov.au)

Food Consumption & Price Elasticity

Simple elasticity estimates have been calculated for each of the categories. Given the relatively short time span (26 quarters of real volume levels, so only 25 quarters of movements) more complicated analysis taking into account potentially confounding factors is not included here.

Using the standard price elasticity definition

$$\varepsilon = \frac{\%\Delta Q}{\%\Delta P}$$

We estimate price elasticity for each category using a simple ordinary least squares regression:

$$dlog(Q) = c + \varepsilon.dlog(P)$$

Where Q is measured using the Chain Volume Measure for the respective category, and P is measured using the Implicit Price Deflator (Current Price divided by Chain Volume Measure) for the category.

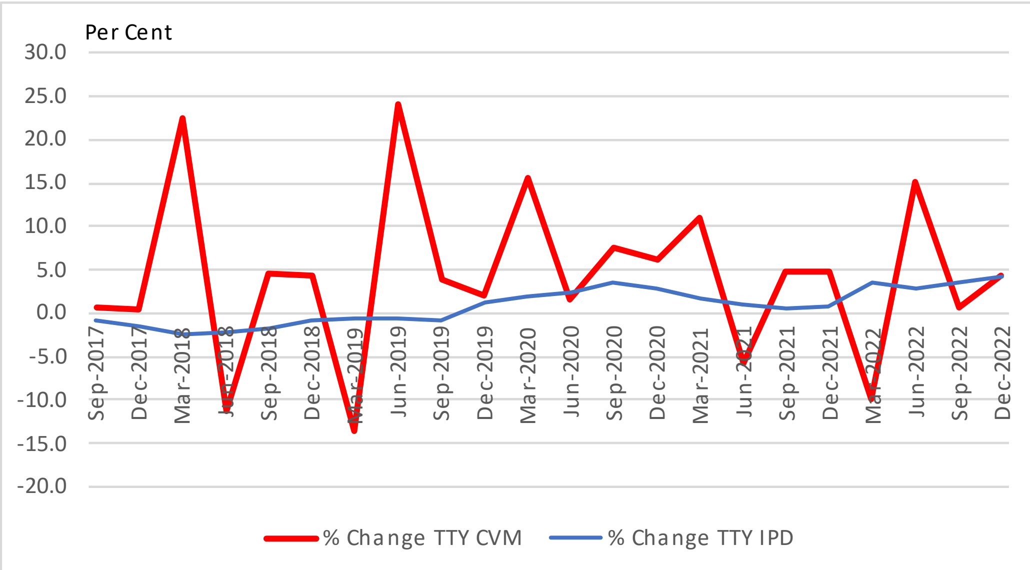
Table 1: Elasticity by SUPC category

SUPC Category	Elasticity	Prob	R-squared
Fresh fruits, vegetables and nuts	-0.68	0.20	0.08
Eggs and honey	0.70	0.33	0.10
Fish; crustaceans and molluscs (excl farmed)	2.45	0.50	0.03
Edible meat, offal and meat products	-1.42	0.07	0.16
Processed seafood	-1.44	0.14	0.11
Dairy products	0.06	0.94	0.03
Processed fruit and vegetable products	-0.27	0.75	0.04
Refined animal oils and fats; vegetable oils and fats	-0.77	0.39	0.03
Grain mill products; pasta and prepared baking mixes	-1.37	0.11	0.11
Bakery products	-0.40	0.67	0.03
Confectionery and sugar	-7.91	0.00	0.67
Other food products	-0.90	0.12	0.16
Non-alcoholic beverages (excl fruit juice and flavoured milk) and ice	-3.05	0.07	0.15

At the SUPC level few of the elasticity relationships are statistically significant, and the R-squared values generally show that prices at this level are not a strong predictor of changes in demand. This is to be expected given the evidence on prices and consumption above. The SUPC level results cover large numbers of individual products, and each period is a full quarter compared to the weekly data in the first section. Both of these factors will mute the price response, as substitution between related goods does not show up, and the discounting cycle is suppressed by the larger time period.

The only exception to this is the ‘Confectionary and Sugar’ category, which has a very significant negative elasticity of -7.91. That is, for every 1% increase in the price of this category there is a 7.91% reduction in demand.

Chart 5: Confectionary and Sugar – change in Chain Volume Measure and Implicit Price Deflator through the year



In general, basic theory would suggest that the more discretionary a good the higher its elasticity. As goods in this product are more likely to be a discretionary 'luxury' piece of consumption it makes sense that elasticity would be high. Goods in this category also have a significant discounting cycle and are relatively non-perishable, which would tend to increase elasticity as there is a greater ability to stockpile at low prices.

One important factor to bear in mind in this analysis is that the underlying data has not been seasonally adjusted. And given the strong seasonal patterns apparent in the underlying data we should be cautious, particularly about the direction of causality. Each year there is a significant increase in consumption during the December quarter, and normally an overall decrease in price. While this is consistent with the price elasticity hypothesis, it would also be consistent with economies of scale allowing producers to reduce prices while increasing supply. It also may reflect a change in elasticity over some periods of the year – at Easter chocolate is less discretionary for families with children expecting easter eggs for instance.

As the SUPC level categories contain a wide range of products, using the more detailed IOPC level categories may provide a better indicator of price elasticity for different categories. With 69 categories we would expect more of these categories would show statistically significant elasticity outcomes.

Table 2: Elasticity by IOPC category – 20 most elastic

IOPC Category	Elasticity	Prob	R-squared
Chocolate confectionery	-7.42	0.00	0.67
Chewing gums, white chocolate, and other confectionery	-7.28	0.00	0.59
Ice cream and frozen confections	-6.54	0.00	0.71
Other fruit and vegetable processing products	-5.89	0.00	0.45
Ice	-4.32	0.02	0.21
Fruit juices, single strength or concentrated	-4.29	0.00	0.47
Almonds and macadamias	-4.20	0.01	0.29
Stone fruit - fresh and sun-dried	-3.81	0.00	0.68
Kiwi fruit	-3.74	0.00	0.81
Soft drink, cordial and syrup	-3.17	0.01	0.26
Berries nec - fresh and sun-dried	-2.60	0.00	0.97
Peanuts	-2.57	0.01	0.28
Edible nutsn ec; Other fruit nec	-2.22	0.02	0.24
Cereal grains and products nec	-2.16	0.00	0.35
Meat pies	-1.99	0.01	0.29
Citrus fruit - fresh and sun-dried	-1.96	0.00	0.81
Strawberries	-1.82	0.00	0.97
Grapes - table	-1.80	0.00	0.77
Coffee and tea, including substitutes	-1.79	0.00	0.35
Cereal foods (incl breakfast foods)	-1.67	0.01	0.26

The highly elastic items fall into three broad categories:

- Non-perishable and frozen products
- Fruit
- Confectionary/dessert items

As discussed above, the price elasticity of fruit likely reflects in part the seasonal production of fruit. During the primary production season for an individual fruit, suppliers are likely to need to lower prices in order to sell their entire production. Production is fixed based on the decisions made on planting in prior seasons (as well as the impact of weather), and for most fruits there is little ability to warehouse product for a future period. As a result, producers will lower prices in order to induce higher demand.

Another factor for fruit is cross-price elasticity. The SUPC level results showed little overall price elasticity for the fruit and vegetable category. This suggests that within the overall category there is a strong degree of substitution between different fruit products. That is, price rises in one fruit are likely to induce demand increases for some other fruit (after accounting for seasonal availability of fruit). This would be consistent with sources such as the dietary guidelines, which treat fruit as a relatively homogenous area of food consumption.[7]

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[7] australian-dietary-guidelines.pdf (health.gov.au)

Table 3: Elasticity by IOPC category – 20 least elastic[8]

IOPC Category	Elasticity	Prob	R-squared
Raw and refined sugar in solid form	-0.94	0.38	0.04
Unblended honey and beeswax	-0.91	0.32	0.04
Refined and processed animal or vegetable oils and fats	-0.90	0.35	0.04
Tomatoes grown undercover	-0.88	0.00	0.75
Olives - fresh and sun-dried	-0.85	0.50	0.03
Beans, french and runner; peas, green or blue grown outdoors	-0.80	0.00	0.53
Potatoes, sweet potatoes and edible roots	-0.70	0.01	0.25
Non-alcoholic beverages nec	-0.56	0.71	0.03
Lettuces grown undercover	-0.49	0.07	0.14
Potato, corn and other crisp products	-0.47	0.24	0.12
Other vegetables (incl. melons), fresh or chilled grown outdoors	-0.47	0.14	0.11
Preserved fruits (incl dried and jams) and fruit products nec	-0.43	0.65	0.01
Other bakery products (excl meat pies)	-0.40	0.78	0.02
Crude soya bean, etc (including margarine)	-0.35	0.26	0.07
Mixes and doughs nec (incl custard powder)	-0.29	0.77	0.01
Bananas - fresh and sun-dried	-0.25	0.00	0.32
Meat (excl fresh) for human consumption	-0.20	0.75	0.02
Bread and bread rolls (excl dough)	-0.16	0.60	0.10
Food products nec	-0.04	0.97	0.00
Vegetables, frozen; pickles and chutney; tomato puree and paste	-0.02	0.98	0.03

The relatively price unresponsive products can be divided into several groups:

- Vegetables and other perishable products such as bread
- Relatively bulky products such as non-alcoholic beverages, where stockpiling to take advantage of discounting is more difficult
- Cooking ingredients such as sugar, doughs, tomato pastes, soya bean etc

One interesting exception to this is the case of bananas, which show a relatively low elasticity compared to other fruits. This may reflect some idiosyncrasy in the measured period, as

[8] Excluding categories with positive measured elasticity

it is inconsistent with the general result from the literature which finds that bananas are relatively price elastic.[9]

Finally, there were a number of categories that had an estimated positive elasticity (that is, price and quantity increase move together). With one exception these estimated elasticities were statistically insignificant (p>0.10).

The one exception to this was the category "Crustaceans, molluscs & aquatic invertebrates", which has an estimated price elasticity of +8.59 (p=0.03). This is an implausibly strong elasticity, but may reflect an underlying response to the very strong seasonal demand increase in the December quarter each year. Demand increases by around 75% each December, while prices increase by an average of 1.8%. Therefore the positive elasticity may be more reflective of the price elasticity of supply, rather than the price elasticity of demand. That is, suppliers may be increasing their prices as they respond to higher demand and face rising marginal costs.

Finally, income represents a potentially confounding variable not considered in any of these elasticity estimates. As both incomes and prices tend to rise over time it's hard to disentangle these effects completely. In general most goods have a positive income elasticity, although some so called 'inferior' goods will fall in consumption with rises in income. Given the short time span it's difficult to provide concrete evidence on income effects. This would be a worthwhile area for future analysis using this dataset once more years of information are available.

[9] THE DEMAND FOR BANANAS AND THE ECONOMIC EFFECT OF SUPPLY RESTRICTION (umn.edu)

Measuring nutritional impacts of changes in food consumption

ABS uses scanner data to estimate the amounts of foods and associated nutrients available from foods sold in the food retail sector. These data are published in the Apparent Consumption of Selected Foodstuffs (ACSF) collection, which commenced in 2018-19 with funding from the then Department of Health. The ACSF allows policy makers and researchers to monitor trends in the consumption of foods over time and among regions. For example, consumption of fruit and vegetables, sweetened beverages, and processed meat are recognised as factors impacting the chronic disease burden.

ACSF methodology

The ACSF incorporates nutrient composition through a coding process in which scanner data food products are assigned 8-digit codes within the AUSNUT 2011-13 food classification system. The AUSNUT 2011-13 was produced by Food Standards Australia New-Zealand and contains nutritional data for over 5000 foods at the lowest level.

During estimation, the weight/volume of scanner data products are weighted to represent the wider food retail sector. The weights are derived from expenditure ratios from the 2015-16 Household Expenditure Survey (HES), stratified by geography (capital city / balance) and food category (around 60 food groups were harmonised between the HES food codes and AUSNUT). To make the weighted estimates, the estimated food expenditure occurring in non-supermarket retail sector is multiplied by the relevant grams per dollar value (which is specific to the product's AUSNUT code and the geographic location) and added to the quantity of food that is supplied by the supermarkets. See ACSF Methodology section for more details on concepts, data sources and methods. The following analysis is based on preliminary estimates that may change once the recent scanner data sales are fully coded to the nutrient database.

Measures of diet quality

The particular foods and patterns of food consumption that are either negatively or positively associated with health have been translated into the 2013 Australian Dietary Guidelines (ADG) which in turn inform public health information material such as the Australian Guide to Healthy Eating. The ADG are accepted as providing the best evidence-based, population level dietary advice[10].

Although the advice in the ADG is intentionally food-centered (because people relate to foods more than nutrients), the recommendations were designed to ensure sufficient levels of nutrients (e.g. vitamins and minerals) according to the requirements published in the 2006 Nutrient Reference Values[11] (NRV). The NRV includes recommendations for the minimum amounts of micronutrients and macronutrients required in the diets of males and females through life stages using measures such as the Estimated Average Requirement (EAR), which is the amount required to meet the needs of half the population and the Recommended Dietary Intake (RDI) which is the daily dietary intake level sufficient to meet the nutrient requirements of nearly all (97–98 %) of healthy individuals[11] above.

Using the ACSF to measure changes in diet quality draws on measures from both the 2013 ADG and the 2006 NRV that can be adapted as indicators to measure change in dietary quality over time in the ACSF.

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[10] National Health and Medical Research Council. (2013). Australian dietary guidelines. Canberra: National Health and Medical Research Council.

[11] National Health and Medical Research Council. (2006). Nutrient reference values for Australia and New Zealand: Including recommended dietary intakes. Canberra: National Health and Medical Research Council

The most suitable dietary indicators for gleaning insights into changes of population-level diet quality are relative measures based on proportions of total energy or ratios per 10k kJ. The major advantage in using a relative measure for comparisons over time is to effectively hold total consumption constant across different periods or places providing a simpler comparison of diet quality.

The relative indicators of diet quality include proportion of dietary energy derived from discretionary foods and proportion of dietary energy derived from free sugars.[12]

Discretionary foods

Guideline 3 from the Australian Dietary Guidelines advises consumers to limit intake of foods containing saturated fat, added salt, added sugars and alcohol. Such foods are called 'discretionary choices' because they are not an essential part of a healthy diet. Examples of discretionary foods include biscuits, cakes, pastries, confectionary, processed meats, potato chips, soft drinks, energy drinks and sports drinks and alcohol.

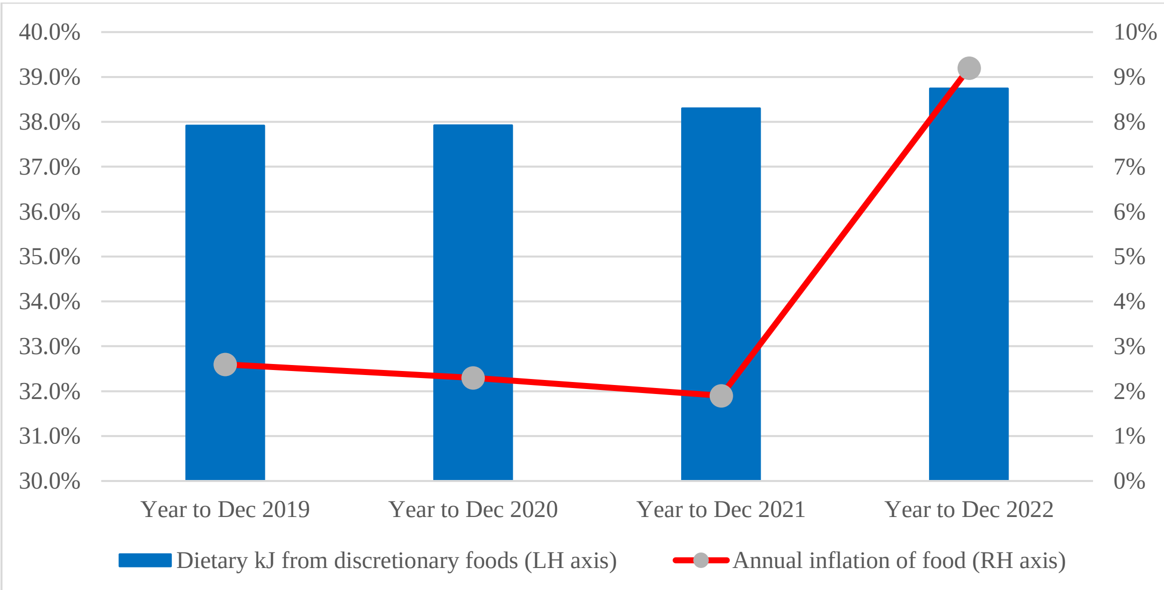
In the three years to December 2021, when food inflation averaged 2.3%[13], discretionary foods contributed an average of 38.0% of total dietary energy available. Then, in the following year when food inflation averaged 9.2%[13] in the 12 months to December, the share of total dietary energy from discretionary foods increased to 38.7%, suggesting an association between higher food inflation and lower quality nutrition. The consumption changes which drove the higher discretionary energy occurred in the context of an overall 297 kJ per capita decline

[12] 'Free sugars' is defined as the total amount of added sugar plus the natural sugar in fruit juice. The WHO recommend that populations derive less than 10% of total energy intake from free sugars.

[13] Percentage change in 'Food and non-alcoholic beverages' index from quarterly CPI, original series

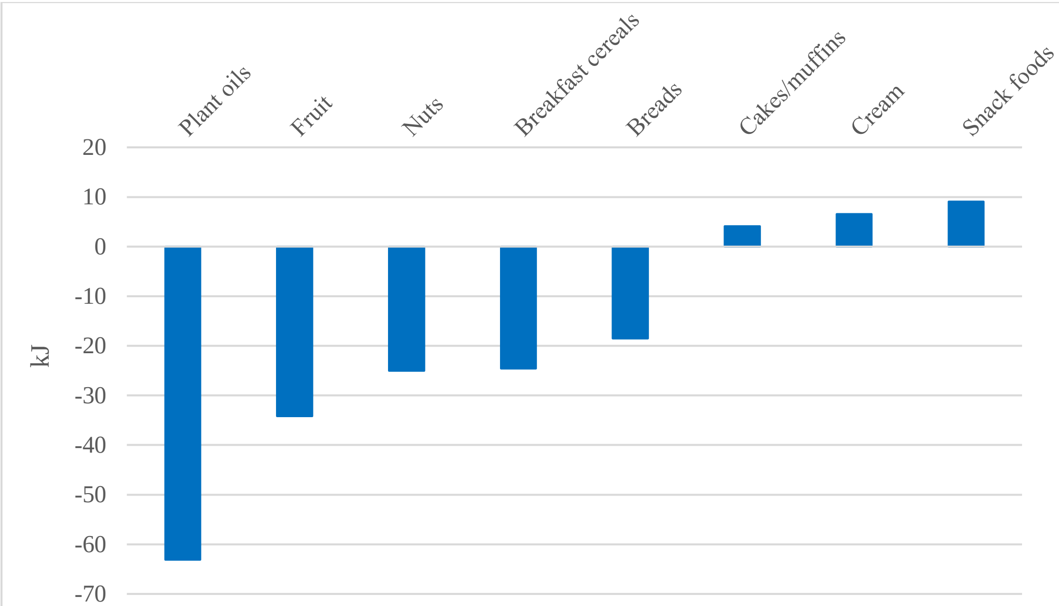
(4.2%), where energy from non-discretionary foods fell faster (4.9%) than energy from discretionary foods (down 3.1% per capita per day).

Chart 6: Proportion of dietary energy from discretionary foods



The foods contributing the greatest declines in per capita non-discretionary energy between 2021 and 2022 included plant oils (-63 kJ), fruit (-33 kJ), dairy milk (-30 kJ), breakfast cereals (-29 kJ), nuts (-22 kJ), bread (-20 kJ), flour, rice and pasta (-18 kJ). Also contributing to the increase in the proportion of energy from discretionary foods were slight increases from snack foods (9.1 kJ), cream (6.6 kJ) and cakes and muffins (4.1 kJ).

Chart 7: Changes in average energy intake for selected food groups, 2021 to 2022

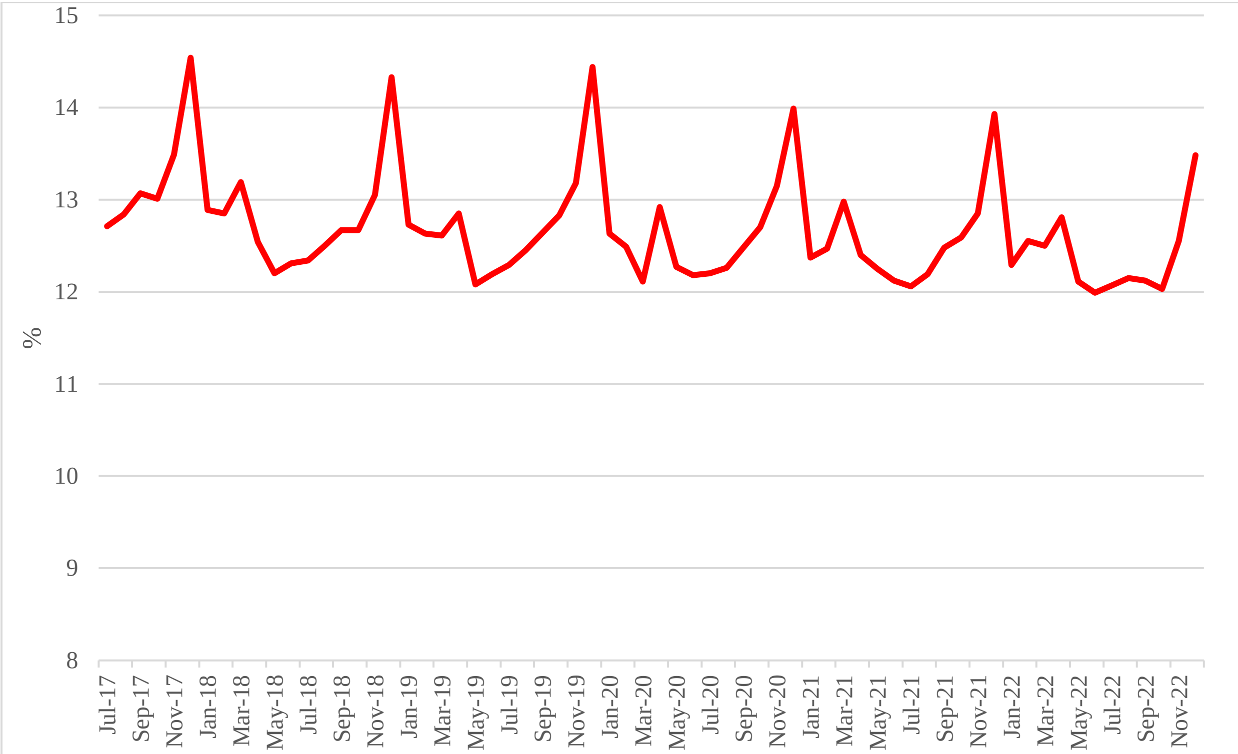


Free sugars

Free sugars includes naturally occurring sugars in fruit juice and the sugars added to foods and beverages. The WHO recommends that populations derive less than 10% of dietary energy from free sugars to reduce the disease burden from dental cavities and metabolic disorders.[12]

In contrast to the uptick in the proportion of discretionary energy seen in 2022, the proportion of energy from free sugars continued its downward trend, driven largely by declining sales of sugar and changing preferences to sugar-free beverages. The soft drink and confectionary sources of free sugars mean that has a strong seasonal pattern characterised by a Christmas peak and a smaller peak each Easter.

Chart 8: Proportion of dietary energy from free sugars



Limitations of Food Scanner Data

The supermarket scanner data described in this paper is an incredibly useful data set, and the ABS hopes to make increasing use of it over time to provide new statistical insights. But there are important limitations that should be considered as well, which point to the ongoing need for other sources of information.

Partial Coverage of Food consumption

The supermarket scanner data the ABS receives makes up around 60-65% of total food consumption on a National Accounts basis. This means that there is only limited information available on more than a third of food consumption on a quarterly basis.

In addition to supermarkets not covered by the scanner data the main food retail businesses are in the meat, fish and poultry retailing and fruit and vegetable retailing classes. There were around 6,600 businesses in these industry classes at the end of 2022.[14] And there are food sales by a wide range of businesses not primarily in the food retailing industries – for instance, service stations, newsagents, and so on.

Different statistics take different approaches to this. In the case of National Accounts, a method has been developed to estimate the total value of food consumption using other sources of data, including quarterly business surveys.

As a result the total expenditure on different products in these non-scanner sources is measured far less frequently. If consumption patterns from these sources differ, particularly if there is substitution between scanner data supermarkets and these sources, there is the potential for increasing measurement error. Using other data sources for confrontation helps to manage this risk – for instance, monitoring relative sales growth between supermarkets and fruit and vegetable retailers.

Don't know if the purchaser is a household

HFCE, CPI and ACFS all aim to measure the household use of food. That is, consumption of food by resident households in Australia. This means that two types of purchases at supermarkets are conceptually excluded:

- purchases by overseas residents (for instance, tourists); and
- purchases by business for intermediate use (for instance, cafes and restaurants)

[14] Counts of Australian Businesses, including Entries and Exits, July 2018 - June 2022 | Australian Bureau of Statistics (abs.gov.au)

In practice it is impossible to separate out these purchases within the supermarket scanner data. The businesses don't know the nature of the purchaser, or the purpose for which the goods have been purchased. Adjustments are made through the National Accounts using other data sources to account for these purchases – for instance, using RBA data on overseas credit cards to estimate purchases by visitors, and using information from surveys of businesses on their purchases.

The lack of detailed product level information on purchaser characteristics could introduce measurement error in terms of expenditure and weights to the extent that an increase in purchases is driven by a change in visitor or business behaviour. This risk is partially mitigated through the use of household surveys, such as the Household Expenditure Survey, which directly measure the consumption of households periodically.

Don't know what type of household the purchaser is in

How consumption of different products is distributed by household type is an important economic and policy question. Understanding, for instance, the consumption of different types of food by income group or source helps to understand the way that changes in tax policy might impact on different households, whether there are differences in the health impacts of food by household composition, and so on.

As scanner data is not linked to any specific household none of these insights can be gathered directly. Some information can be gathered directly by examining the correlation of consumption between geographic areas by different demographic and income characteristics. But this can only give a partial story.

This shows the continuing need for other data sources to answer these key economic and policy questions.

Conclusion

Use of scanner data across the ABS has enabled significant improvements in statistical methods and measurement of important variables such as the CPI. In addition to reducing the cost of data gathering the greater detail available has allowed for more detailed, more frequent information on consumption to be produced, and allowed the CPI to reflect changes in expenditure weights in real time.

These datasets provide a new window into consumer behaviour previously not available at this whole-of-economy level. Further work will help to provide new insights that can help to develop the economics of consumer behaviour, and to help policy makers understand the impacts of changes on a critical area of household expenditure.