Estimating demand for competition analysis

A statistical exploration, and some possible applications

Report to the Productivity Hub by NZIER, with the assistance of Cognitus Economic Insight

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About the Productivity Hub

The Productivity Hub was a partnership of agencies that funded this research. The Productivity Hub agencies consisted of the Ministry of Business, Innovation and Employment, the Productivity Commission, the Commerce Commission, Stats NZ, and the Treasury.

Authorship

This report was prepared by Dr Eilya Torshizian of NZIER, with the assistance of Dr Richard Meade of Cognitus Economic Insight.

It was quality approved by Peter Wilson.

The assistance of Sarah Spring is gratefully acknowledged.

Registered office: Level 13, Willeston House, 22–28 Willeston St | PO Box 3479, Wellington 6140
Auckland office: Ground Floor, 70 Shortland St, Auckland
Tel +64 4 472 1880 | econ@nzier.org.nz | www.nzier.org.nz

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Key points

The Productivity Hub commissioned NZIER, along with Cognitus Economic Insight, to study how analysis of consumer demand can aid competition analyses.

The purpose of the Project was to demonstrate the value of using an “Almost Ideal Demand System” (AIDS) approach to estimate household demand for a subset of key expenditure categories. The specific tasks we were commissioned to undertake were:

- to establish the feasibility of estimating demand in selected expenditure classes using administrative data available in New Zealand using the AIDS; and
- to explore the applicability of the AIDS model estimates for competition and wider policy analyses.

The Project is exploratory, seeking to establish the feasibility of an estimation technique data. As such, the outputs of the model should be regarded as indicative only.

Estimation of own- and cross-product elasticities provides valuable information for competition studies

Estimates of demand elasticities can be used to inform the following issues in competition analysis:

- Whether a proposed merger is likely to cause consumer-harming price *increases*
- To define the relevant market for competition analysis
- Excess profitability and hence otherwise unobservable marginal production costs.

The AIDS model is both possible and appropriate within the New Zealand context

We have been able to use the data in Stats NZ’s database to estimate own and cross-product price elasticities for the major groups we studied, broken down by geographical area.

While this is an exploratory study, we find most of our results are robust and we recommend that using the AIDS modelling approach be considered for future studies of demand.

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1 Introduction

In 2017, the Productivity Hub (the Hub) requested proposals from economic consultants to undertake empirical analysis of competition-related issues in New Zealand. NZIER, along with Cognitus Economic Insight (together, the NZIER team), proposed a number of new approaches to answer the questions posed by the Hub. Following consultation, we were engaged by the Hub to study how analysis of consumer demand can aid competition analyses (the Project).

This report contains the results of that study.

We start with a conceptual discussion of the role of demand studies, and the role of demand in competition studies, to provide context for the analysis.

We then outline the various approaches that have been used by researchers to incorporate analysis of demand into competition and productivity studies. One particularly common method of estimating demand – the Almost Ideal Demand System (AIDS) model developed by Nobel prize-winning economist Angus Deaton, and co-author John Meullbauer, in 1980 – is then discussed in detail.

Next we show how we used the AIDS model to study demand in a number of selected categories of goods and services in New Zealand. Particular focus is placed on the issue of using currently available data collected by Statistics NZ for specific purposes – the Household Expenditure Survey (HES) and the Consumers Price Index (CPI).

Finally, we present the detailed results of our analysis of demand in three separate markets: electricity, motor fuels and a range of "pleasure purchases".

While preliminary in nature, our study suggests that using the AIDS model is both possible and appropriate within the New Zealand context.

We conclude with recommendations for further study.

1.1 Project context and purpose

The purpose of the Project was:

- to establish the feasibility of estimating AIDS demand models for selected expenditure classes using administrative data available in New Zealand, and
- to explore the applicability of AIDS model estimates for competition and wider policy analyses.

The Project is exploratory, seeking to establish the feasibility of estimating AIDS demand models using available administrative data. As such, the outputs of the model should be regarded as indicative only.

The NZIER team has not been asked to provide demand estimates to inform any specific decision and cannot warrant that they are fit for any purpose other than establishing the feasibility of AIDS estimation using available data. If the Hub or any other agency would like fit-for-purpose demand estimates for some specific policy question or decision context, such demand estimates should be produced from further research undertaken with that question or context in mind.

2 Why estimate demand?

According to Davis and Garcés (2010), in their comprehensive survey of quantitative techniques for competition (i.e. antitrust) analysis:

> *"The analysis of demand is probably the single most important component of most empirical exercises in antitrust investigations. It is impossible to quantify the likelihood or effect of a change in firm behaviour if we do not have information about the potential response of its customers."*[1]

Estimating demand enables estimation of key economic variables such as products' own- and cross-price elasticities, essential for determining whether any two goods or services are substitutes or complements. Elasticities inform, for example:

- Whether a proposed merger is likely to cause consumer-harming price *increases* (e.g. when merging monopolies produce substitutes) or consumer-benefitting price *reductions* (when they produce complements)
- Defining the relevant market for competition analysis – e.g. using diversion ratios, 'hypothetical monopolist tests' (HMTs), or 'small, non-transitory but significant increase in price' (SSNIP) tests[2]
- The estimation of measures of excess profitability (price-cost margins, or PCMs), and hence also estimation of otherwise unobservable marginal production costs (without needing to use highly imperfect accounting-based measures). Marginal cost estimates derived from differing assumptions about firm conduct, in turn, can be used to infer whether firms are behaving competitively or collusively.

Demand estimation also lies at the heart of measuring the welfare impacts of mergers, policies, etc. Whether welfare is measured in terms of just consumer surplus, or in terms of total surplus (i.e. the sum of consumer surplus and firms' profits), understanding demand is essential for being able to do more than just qualitatively assess welfare, or in modern usage, 'wellbeing' (taking wellbeing to mean welfare in the conventional economic sense). Demand estimation also enables estimation of more 'exact' consumer welfare measures such as equivalent variation (EV) and compensating variation (CV).

Importantly, sophisticated demand estimation techniques can shed light on consumer willingness to pay (WTP) for both price and non-price characteristics of goods or services, which is especially useful for analyses involving non-traded (e.g. environmental or cultural) goods or services.

Demand estimation, therefore, opens numerous possibilities for more objective and quantitative competition, policy and regulatory analyses. It helps to reduce – if not remove – the need for subjective or qualitative analyses. It represents a valuable tool for making evidence-based policies or decisions – or for scrutinising such policies or decisions.

1 Davis, P. and E. Garcés, 2010, *Quantitative Techniques for Competition and Antitrust Analysis*, Princeton University Press, p. 1.

2 HMTs and SSNIP tests are described further in Section 2.1. For a full discussion of market definition techniques, see Davis, P. and E. Garcés, 2010, *Quantitative Techniques for Competition and Antitrust Analysis*, Princeton University Press, Chapter 4.

2.1 Market definition

Davis and Garcés (2010) survey a range of approaches used for defining markets in competition analyses.[3] Market definition can be particularly important when form- or structural-based tests are applied in competition analyses (e.g. mergers). These include tests for which market shares are of particular interest, such as market concentration measures like the Herfindahl-Hirschman Index (HHI). It can be less critical, though, in effects-based tests, which focus more on whether any given transaction (e.g. a merger) is likely to result in increased prices.

For present purposes we will focus on SSNIP tests, since they illustrate how demand model estimates can be relevant to market definition. SSNIP tests are a particular implementation of a wider class of approaches for measuring pricing constraints on firms called 'hypothetical monopoly tests' (HMTs), which construe a market as a collection of products or services "worth monopolising". Unlike SSNIP tests, which consider only price changes, HMTs also allow for non-price measures such as advertising or quality competition that firms might employ to make a collection of products or services worth monopolising.

SSNIP tests assume that a market can be defined in terms of the products or services that – as a collection – do not face *pricing* constraints from other products or services. If a hypothetical monopolist of a candidate market definition does not find it profitable to increase prices by 5-10% for a year, then this means there must be at least one significant substitute product not included in that definition which consumers can switch to in response to the price increase. In turn this means the candidate market definition is too narrow, and should be successively expanded until it includes all such other significant products.

Illustrating the single-product case,[4] Davis and Garcés (2010) show that it will be profitable for a monopolist with constant marginal cost c to hypothetically increase its price from p_0 to p_1 (i.e. by 5-10%) if its resulting price-cost margin, PCM_1, is less than the inverse of its own-price elasticity of demand ($\eta_{11} > 0$), i.e. if:

$$PCM_1 \equiv \frac{p_1 - c}{p_1} \leq \frac{1}{\eta_{11}}$$

This shows how demand estimation can produce estimates of parameters (here, own-price elasticity) relevant to market definition.

2.2 Price-cost margins, marginal cost, and competitive conduct

2.2.1 Why are price-cost margins and marginal cost of interest?

Price-cost margins, or PCMs – if measured well – provide information about firm profitability. That information can be:

- Useful in its own right – e.g. helping to judge whether firms are making unduly high profits

[3] Davis, P. and E. Garcés, 2010, *Quantitative Techniques for Competition and Antitrust Analysis*, Princeton University Press, Chapter 4.

[4] For the differentiated multi-product case, see Davis, P. and E. Garcés, 2010, *Quantitative Techniques for Competition and Antitrust Analysis*, Princeton University Press, Chapter 4.6.3.

- Used to estimate unobservable marginal costs.

In turn, the latter is useful for things like:

- Exploring whether firms are profit-maximising – this requires that a firm's marginal revenue (which can be inferred from demand equations) equals marginal cost
- Assessing firm efficiency or productivity
- Analysing firms' competitive conduct.

While profit-maximising perfectly competitive firms will set price equal to marginal cost and thus have a PCM equal to zero, observing that a given firm has a PCM greater than zero tells us very little about whether it is behaving uncompetitively. This is especially if there are technical or other reasons why the market in question cannot sustain a large number of firms (e.g. because production involves large economies of scale). Instead, the relevant question in such industries is not whether the firm in question has a positive PCM, but whether its PCM is higher than it ought to be. That assessment hinges on whether there is some feasible alternative set of market arrangements yielding a lower PCM.[5]

Estimating PCMs using estimated demand parameters requires an assumption about underlying firm conduct. In this sense demand-based PCM estimates are 'structural'. The approach involves assuming that a firm competes in some specified manner, in which case the first order condition from the firm's profit-maximisation problem enables the firm's PCM to be expressed as a function of price elasticities of demand. For example, for a single product monopolist, the relevant expression is as in Section 2.1 above, but with price-maximising p^* taking the place of hypothetically-increased price p_1, i.e.:

$$PCM^*_{Monopoly} \equiv \frac{p^*_{Monopoly} - c}{p^*_{Monopoly}} = \frac{1}{\eta_{11}}$$

For other competitive assumptions, alternative expressions are derived. For example, assuming an industry has n symmetric firms competing by simultaneously choosing output quantities (i.e. competing a la Cournot), in a homogeneous single product industry, the relevant PCM is:

$$PCM^*_{Cournot(n)} \equiv \frac{p^*_{Cournot(n)} - c}{p^*_{Cournot(n)}} = \frac{1}{n \times \eta_{11}}$$

Supposing we have an estimate of own-price elasticity from our demand model, $\hat{\eta}_{11}$, and observe the relevant product price, then marginal cost can be 'structurally' estimated by solving for c in the above expressions. For example, in the monopoly case, and recalling that $\hat{\eta}_{11} > 0$ (i.e. a 1% increase in own-price results in an $\hat{\eta}_{11}$% *decrease* in own-demand), rearranging the above monopoly PCM enables marginal cost to be estimated as:

$$\hat{c}_{Monopoly} = p - \frac{p}{\hat{\eta}_{11}}$$

[5] For an application of this idea in the context of assessing whether liquid fuel prices are reasonable, see Section 3 of Cognitus Economic Insight, NZIER, and Grant Thornton, 2017, *New Zealand Fuel Market Financial Performance Study*, report prepared for the Ministry of Business, Innovation and Employment.

2.2.2 Why use demand-side estimates rather than accounting-based estimates?

The demand-side estimates of PCMs and marginal costs described above suffer from possible biases arising from:

- Mis-estimating demand elasticities – e.g. due to using bad data, a poor demand specification, or failing to account for estimation issues (e.g. price endogeneity); or
- Mis-specifying the relevant form of competitive conduct – e.g. assuming firms compete in quantities (i.e. a la Cournot) when they compete in prices (i.e. a la Bertrand).

They have the merit, however, of being inferred from actual market data. They also enable inquiry into competitive conduct (see Section 2.2.3 below).

A commonly-used alternative to such a structural approach for estimating PCMs is the accounting-based approach.[6] For example, PCMs are estimated using average non-fixed (i.e. variable) costs in place of unobservable and hence un-measured marginal costs. This has the advantage of simplicity, since it can be implemented using readily available accounting data, but suffers from various measurement problems. Using average total costs (i.e. including fixed as well as variable costs) is simply inappropriate, while even variable costs can be mis-estimated. This is especially when they are multi-period costs (e.g. R&D costs, or capital charges), or if accounting (or tax) depreciation rates are used instead of 'economic' depreciation rates.[7]

Such mis-specifications can produce materially-biased estimates. Also, because they are not predicated on any specific form of competitive conduct, accounting-based PCMs and marginal cost estimates do not lend themselves to inquiring into firms' competitive conduct.

2.2.3 Illustrating how price-cost margins tell us about competitive conduct

A common interest of competition analysis is assessing whether firms are behaving competitively or uncompetitively.[8] As mentioned in Section 2.2.1, the most relevant question is not whether firms in an industry that is inherently imperfectly competitive are behaving uncompetitively, but more uncompetitively than they need to be. Estimated PCMs can provide the analyst with information about firm conduct, which informs such an assessment.

The basic approach is as follows:[9]

1 Estimate price elasticities of demand using a demand model such as an AIDS model (but preferably a discrete choice demand model that allows for heterogeneous consumer tastes, see Section 3.1)

6 Other alternatives include direct estimation of firm cost functions, or 'engineering-based' approaches.

7 For a discussion of problems with accounting-based PCM estimation, see Chapter 8 of Carlton, D. and J. Perloff, 2015, *Modern Industrial Organization*, 4 ed., Pearson.

8 This should be expected to be a common focus of market studies under the Commerce Commission's recent market studies powers.

9 For a fuller discussion, see Section 6.3 of Cognitus Economic Insight, NZIER, and Grant Thornton, 2017, *New Zealand Fuel Market Financial Performance Study*, report prepared for the New Zealand Ministry of Business, Innovation and Employment, May.

2 Combine these estimates with models of firm behaviour to estimate PCMs under the assumed modes of competition (price- or quantity-based oligopolistic competition, collusion, etc.)

3 Reverse out estimates of marginal production costs from estimated PCMs under each assumed mode of competition

4 Use data on drivers of costs (e.g. crude oil prices in the case of retail fuels, hydro lake levels and/or wholesale gas prices for electricity) to statistically estimate marginal costs

5 Apply statistical tests to discern which assumed mode of competition generates marginal cost estimates most consistent with the data.[10]

For example, marginal costs in step 3 might be:

1 As implied by n-firm Cournot competition, which from Section 2.2.1 above (rearranging the expression for $PCM^*_{Cournot(n)}$) is:

$$\hat{c}_{Cournot(n)} = p - \frac{p}{n \times \hat{\eta}_{11}}$$

2 As implied by perfect collusion, which is the same as monopoly, in which case the relevant estimate of marginal cost is also as in Section 2.2.1 above:

$$\hat{c}_{Monopoly} = p - \frac{p}{\hat{\eta}_{11}}$$

Step 5 above then indicates whether the marginal costs estimated assuming (e.g.) collusion are more consistent with cost driver data than (e.g.) n-firm oligopolistic competition. This provides a statistical basis for inferring anticompetitive conduct, without needing to have access to firms' inside information (or other 'smoking guns').

Indeed, such an approach could be used as a statistical 'screen' to identify whether the Commerce Commission should proceed to use its powers for accessing firms' confidential data. It might use those powers if it appears that firms in a given industry are behaving collusively (or otherwise uncompetitively – e.g. behaving like a duopoly rather than an n-firm oligopoly when the industry has $n > 2$ firms) based on such a statistical screen.

2.3 Welfare analysis

2.3.1 Why estimate welfare?

It is not uncommon in competition or regulatory analyses of imperfectly-competitive industries to focus on cost drivers at a quantitative level, but address demand-side issues more qualitatively. This is natural, since it is much easier to obtain data on industry (average, if not marginal) costs. However, focusing unduly on the cost side of an industry overlooks the point that profit maximising firms' behaviours will hinge on equating marginal costs with marginal revenues. Demand estimation is useful because:

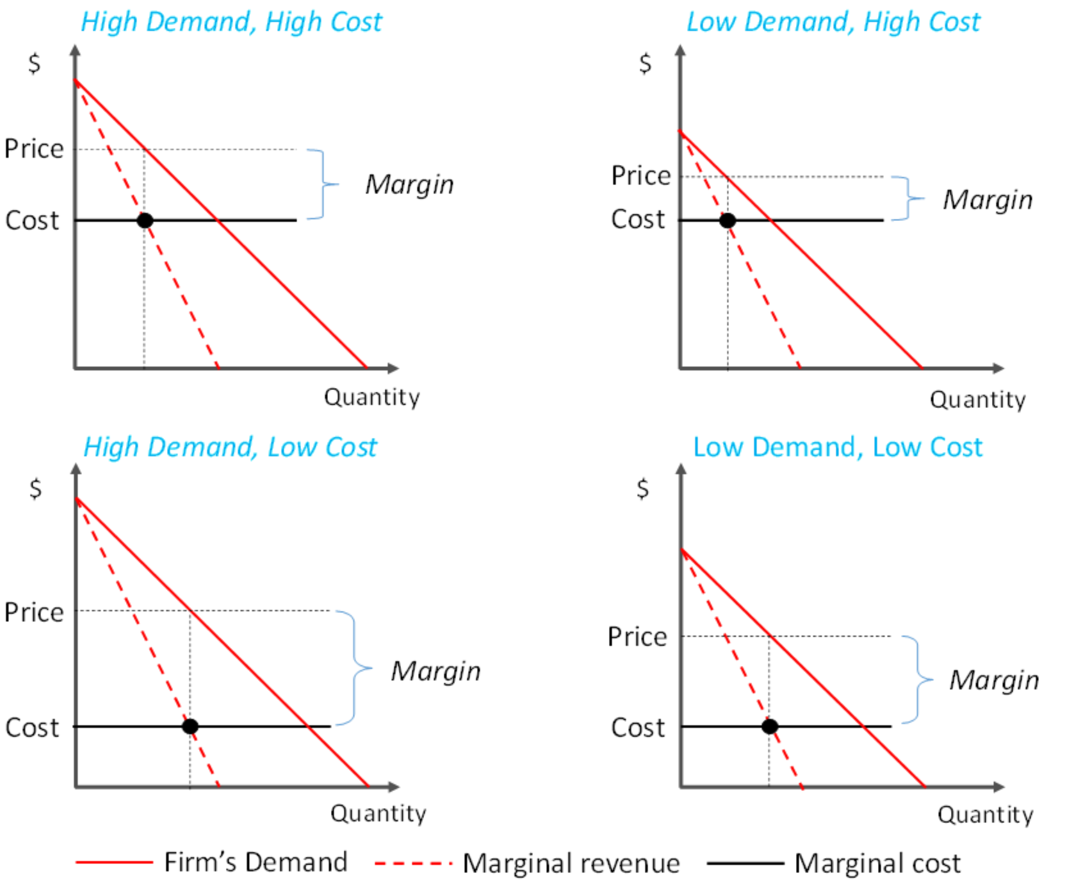
- It provides a means for estimating marginal costs, which are unobservable

[10] For a detailed example, see this approach applied in a study of the French bottled water industry, in Bonnet, C. and P. Dubois, 2010, "Inference on Vertical Contracts between Manufacturers and Retailers allowing for Nonlinear Pricing and Resale Price Maintenance", *RAND Journal of Economics*, 41(1), Spring, 139-164.

- It also provides information relevant to estimating marginal revenue.

Figure 1, taken from the 2017 fuel market study,[11] illustrates how firms facing the same marginal costs will choose quite different profit-maximising prices (and hence margins) depending on the demand conditions they face. Focusing just on the supply side (i.e. costs) is insufficient to make this distinction.

Figure 1 Price determination depends on demand as well as costs



Source: Figure 20 from Cognitus Economic Insight, NZIER, and Grant Thornton, 2017, *New Zealand Fuel Market Financial Performance Study*, report prepared for the New Zealand Ministry of Business, Innovation and Employment, May.

However, demand estimation offers a more direct route to assess the desirability of competition (e.g. merger clearance) or other regulatory or policy choices (i.e. new policies or taxes, etc.). Specifically, with evidence about demand characteristics, it is possible to directly estimate measures of consumer welfare. We now discuss one such approach based on the AIDS model.

[11] Cognitus Economic Insight, NZIER, and Grant Thornton, 2017, *New Zealand Fuel Market Financial Performance Study*, report prepared for the New Zealand Ministry of Business, Innovation and Employment, May.

2.3.2 How welfare can be estimated using an AIDS model – compensating variation

An exact measure of welfare, at an individual household level, can be obtained using the standard microeconomics notion of 'compensating variation' (*CV*). In the case of measuring welfare, changes from a change in one or more prices (e.g. introduction of new consumption taxes), CV is defined to be the change in income required to restore a given household to their utility level enjoyed prior to the price change(s).[12]

In general terms, CV is calculated as the difference in household expenditure functions before and after the price under consideration:

$$CV = e(p_0, u) - e(p_1, u)$$

Here, $e(.)$ is the expenditure function, defined as being the minimum amount of money the household needs to spend in order to achieve a given initial utility level u taking all prices as given. Prices in this case are price vectors, with p_0 being the vector of relevant prices prior to the change in one or more prices being evaluated, and p_1 is the vector of prices following such change(s).

If a household is maximising utility, its initial expenditure level is the same as its total income level (i.e. it is spending all its income). However, if only a subset of household expenditures is being analysed instead of total household expenditure, then the household's initial expenditure level equals its total expenditure on that subset.[13] Denoting the relevant income (or expenditure) level as y, this means CV in relation to a change in price or prices can be expressed as:

$$CV = y - e(p_1, u)$$

AIDS demand models enable direct estimation of $e(p_1, u)$. An advantage of using an AIDS model to estimate CV, instead of a random utility-based model (see Section 3.1), is that the latter typically assumes a constant marginal utility of income when estimating welfare. AIDS models do not need to impose that restriction.[14]

Specifically, the <u>log</u> expenditure function for an AIDS specification with price vector p and utility level u is:

$$m(p, u) \equiv ln\big(e(p, u)\big) = \ln a(p) + u\beta_0 \prod_i p_i^{\beta_i}$$

where:

$$\ln a(p) = \alpha_0 + \sum_i \alpha_i \ln p_i + \frac{1}{2} \sum_i \sum_j \gamma_{ij} \ln p_i \ln p_j$$

The parameters α, β and γ are replaced using the AIDS model estimates, while unobservable u is replaced using the value of indirect utility at initial prices p_0, where indirect utility writes as (using $\ln a(p)$ from above):

12 CV can also be defined for other changes affecting household utility, such as quality changes. For an application of AIDS models for estimating CV in response to quality changes, see Shaikh, S. and D. Larson, 2003, "A Two-Constraint Almost Ideal Demand Model of Recreation and Donations", *The Review of Economics and Statistics*, 85(4), November, 953-961.

13 These two cases respectively correspond to the 'incomplete' and 'partial' demand systems approaches discussed in Shaikh, S. and D. Larson, 2003, "A Two-Constraint Almost Ideal Demand Model of Recreation and Donations", *The Review of Economics and Statistics*, 85(4), November, 953-961.

14 Shaikh, S. and D. Larson, 2003, "A Two-Constraint Almost Ideal Demand Model of Recreation and Donations", *The Review of Economics and Statistics*, 85(4), November, 953-961.

$$V(p,y) = \frac{\ln y - \ln a(p)}{\beta_0 \prod_i p_i^{\beta_i}}$$

With u estimated this way (the resulting estimate denoted $\hat{u}$), the log expenditure function $m(p,u)$ can be evaluated using $\hat{u}$ and the changed price vector p_1. The expenditure function following the price change(s) can then be evaluated as $e(p_1,\hat{u}) = exp\big(m(p_1,\hat{u})\big)$, from which we compute the required CV.

Thus demand estimates obtained from AIDS model estimations can be used to compute *CV* for a change in one or more prices (or consumption taxes). This estimate of the welfare impact of the price change(s) can be aggregated over households to estimate the total welfare effect of the change. Because CV is defined to be a required change in income, it is already a monetary metric that can be compared with other monetary metrics. This means *CV* estimated this way be directly used in cost-benefit analyses, merger simulations, etc.

3 How to estimate demand

3.1 Two main approaches

The two main approaches for estimating demand involve estimation in either the:[15]

1 Products space – i.e. estimating demand for particular goods or services (or expenditure classes) or

2 Characteristics space – i.e. decomposing goods or services into a collection of price and non-price characteristics.

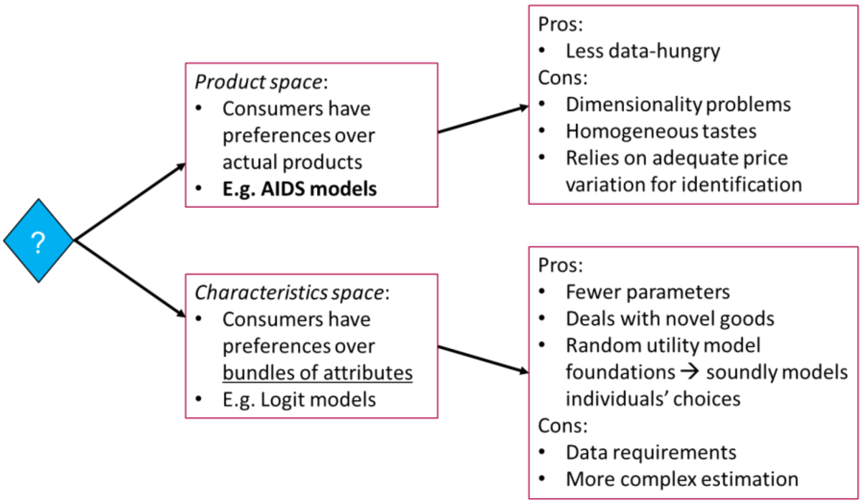
AIDS models fall into the former category, while discrete choice demand analysis based on random utility models fall into the latter.[16]

Figure 2 compares these two broad approaches for demand estimation.

[15] For a comprehensive discussion of demand estimation approaches, see Ackerberg, D., Benkard, C. L., Berry, S. and A. Pakes, 2007, “Econometric Tools for Analyzing Market Outcomes”, in Heckman, J. and E. Leamer, *Handbook of Econometrics*, Volume 6A, Elsevier, 4171-4276.

[16] For a high-level introduction to discrete choice demand analysis, see Chapter 9.2 of Davis, P. and E. Garcés, 2010, *Quantitative Techniques for Competition and Antitrust Analysis*, Princeton University Press. For a more thorough introduction, see Train, K., 2009, *Discrete Choice Methods with Simulation*, 2 ed., Cambridge University Press.

Figure 2 Comparing products space and characteristics space demand approaches



Source: NZIER and Cognitus Economic Insight.

A key limitation of the products space approach is that it quickly encounters problems of dimensionality, with the number of required parameter estimates rising exponentially with the number of products. This limits the number of products that can be incorporated in any demand model estimation. Relatedly, estimation requires sufficient price variation to identify demand parameters. Also, products space models model aggregate demand, so cannot tell the researcher much about consumer heterogeneity (e.g. household-level taste differences), despite using consumer-level data.

The characteristics space approach decomposes an arbitrary number of products or services into a finite number of characteristics, which overcomes the dimensionality problem of products space models. Another advantage of the characteristics space approach is that it can explicitly allow for differences or changes in product quality, and can estimate demand for products or services that do not yet exist (but whose combination of characteristics can be described). Finally, since characteristics space models are founded on individual-level decision-making (using the random utility model), they can accommodate heterogeneity in consumer-level tastes, and thus estimate demand parameters for different classes of consumer.

In principle these considerations suggest that estimating demand in characteristics space should generally be preferred. However, a key limitation of characteristics space demand models are that they require much more granular data. Specifically, they need not just prices and quantities consumed, generally at the individual consumer level, but also the non-price characteristics of the relevant products or services, as well as price and non-price characteristics of alternatives not chosen by consumers.[17]

Thus, an enduring advantage of product space demand models, despite their dimensionality issues, is that they require much simpler data. While, ideally, individual or

[17] An important exception is discrete choice demand models needing only market-level data – the so-called "BLP" technique for estimating random coefficient (or mixed) logit models. For the seminal study, see Berry, S., Levinsohn, J. and A. Pakes, 1995, "Automobile Prices in Market Equilibrium", *Econometrica*, 63, 841-890.

household-level data should still be used, price and quantity (or expenditure) data is required, but not data on non-price characteristics.

3.2 The Almost Ideal Demand System model

The AIDS model was developed by Nobel Laureate Angus Deaton and co-author, John Meullbauer, in 1980.[18] The AIDS demand model is a commonly-used method in empirical demand analysis. It has been applied in numerous studies of household demand and continues to be applied even though it is almost 40 years old.

The AIDS model allows researchers to treat aggregate consumer behaviour as if it were the outcome of a single maximising consumer.

A key advantage of the AIDS approach is that it relies on price and expenditures data, with the latter, often collected for administrative purposes. Also, AIDS models have the desirable property that they can be aggregated – if any given household's demand corresponds to the AIDS specification, then aggregating across such households produces aggregate demand that also corresponds to the AIDS specification.[19]

The purpose of the Project was to estimate demand using available administrative data, rather than to create novel datasets. We chose to estimate a products space model of demand along the lines of the AIDS model (absent better data, we were limited to estimating such a model). Further motivation for this approach was provided by the fact that prior New Zealand research demonstrated the feasibility of estimating demand using New Zealand administrative data for a variety of food expenditure classes.[20] In the Project we wanted to explore how much more widely the AIDS approach could be applied using administrative data available in New Zealand.

3.3 Possible endogeneity issues

AIDS demand models are commonly estimated on the assumption that prices are exogenous. This means that researchers set aside the simultaneous equation bias that can arise when price determination arises from the interaction of supply and demand. Commonly this exogeneity assumption is defended on the basis that households are price takers. However, this ignores the possibility that households make their consumption decisions based on supplier actions such as price-discounting or other promotions. Additionally, household expenditures might also suffer from endogeneity issues.[21]

Failing to account for price or expenditure endogeneity issues could result in biased and inconsistent estimates of demand model parameters, and hence of decision-relevant metrics such as price elasticities.[22] This is more likely to be a risk for models of demand for differentiated products,[23] and might even be more pronounced in macro-level demand

18 Deaton, A. and J. Muellbauer, 1980 "An Almost Ideal Demand System." *The American Economic Review*, 70(3), pp 312-326.

19 Deaton, A. and J. Muellbauer, 1980 "An Almost Ideal Demand System." *The American Economic Review*, 70(3), p. 314.

20 Mhurchu, C., Eyles, H., Schilling, C., Yang, Q., Kaye-Blake, W., Genc, M. and T. Blakely, 2013, "Food Prices and Consumer Demand: Differences across Income Levels and Ethnic Groups", *PLOS ONE*, 8(10), October, e75934. doi:10.1371/journal.pone.0075934.

21 Dhar, T., Chavas, J.-P. and B. Gould, 2003, "An Empirical Assessment of Endogeneity Issues in Demand Analysis for Differentiated Products", *American Journal of Agricultural Economics*, 85(3), August, pp 605-617.

22 Hovhannisyan, V. and M. Bozic, 2017, "Price Endogeneity and Food Demand in Urban China", *Journal of Agricultural Economics*, 68(2), pp 386-406.

23 Dhar, T., Chavas, J.-P. and B. Gould, 2003, "An Empirical Assessment of Endogeneity Issues in Demand Analysis for Differentiated Products", *American Journal of Agricultural Economics*, 85(3), August, pp 605-617.

analyses than in disaggregated (e.g. household-level) models.[24] Where such endogeneity issues are suspected to be material, there is merit in adapting the demand model estimation to account for this.

One approach for dealing with price and expenditure endogeneity issues is to use instrumental variables techniques. Specifically, reduced-form regressions are added, such as regressions of prices against supply shifters (such as weather shocks, which are relevant for agricultural production in particular).[25] Finding valid instruments for prices can be challenging, and standard instrumental variables approach cannot be used when models are non-linear. Alternative approaches such as (full information) maximum likelihood must be used.

Fully exploring endogeneity issues has proved beyond the scope of the Project. This is because of the data issues we encountered even for AIDS model estimation under the simplifying assumption that prices are exogenous. It is also because we have not estimated demand with any specific policy question in mind, and cannot judge the materiality of addressing endogeneity issues for a specific application. We simply flag that endogeneity might be considered a material issue in any given demand model application, and leave it to any such future research to identify and resolve endogeneity issues as appropriate.

4 Details of the model that we estimated

We estimated a standard (Linear Approximation of the) Almost Ideal Demand System (LA-AIDS):

$$w_{ir} = a_i + \sum_{j=1}^{N} \gamma_{ij} \ln(p_{jr}) + \beta_i \ln(\frac{x_r}{P_r}); \quad (1)$$

where, w_{ir} is the budget share of good i in region r; p_{jr} is the price of product j in region r; x_r is the total expenditure in region r; P_r is the Stone Price index[26]:

$$\log(P_r) = \sum_i w_{ir} \ln(p_r) \quad (2)$$

Equation 1 shows a system of demand functions with the sum of total expenditure (w_i) being equal to 1. This condition holds if

$$\sum_{i=1}^{n} \alpha_i = 1, \sum_{i=1}^{n} \gamma_{ij} = 0, \sum_{i=1}^{n} \beta_i = 0 \quad (3)$$

The ‘homogeneity’ condition ensures that there is no money illusion:

24 Hovhannisyan, V. and M. Bozic, 2017, “Price Endogeneity and Food Demand in Urban China”, *Journal of Agricultural Economics*, 68(2), pp 386-406.

25 Hovhannisyan, V. and M. Bozic, 2017, “Price Endogeneity and Food Demand in Urban China”, *Journal of Agricultural Economics*, 68(2), pp 386-406; and Dhar, T., Chavas, J.-P. and B. Gould, 2003, “An Empirical Assessment of Endogeneity Issues in Demand Analysis for Differentiated Products”, *American Journal of Agricultural Economics*, 85(3), August, pp 605-617.

26 Stone, Richard. (1953). *The Measurement of Consumers’ Expenditure and Behaviour in the United Kingdom, 1920-1938*. Cambridge University Press.

$$\sum_j \gamma_{ij} = 0, \gamma_{ij} = \gamma_{ji} \tag{4}$$

The demand functions are homogeneous of degrees zero in prices and total expenditure taken together – this satisfies Slutsky symmetry (on the matrix of compensated price response).

Review of the concept – Slutsky equation, Marshallian and Hicksian demand

The Slutsky equation implies that the total (Marshallian) price effect is equal to the sum of the substitution effect and an income effect.

The Uncompensated (Marshallian) demand curve shows how demand for a good changes when prices change, holding income constant.

The compensated (Hicksian) demand curve shows how demand changes when price changes, holding utility constant.

The expenditure (income) elasticities of the AIDS model can be derived from the Marshallian (uncompensated) demand functions (1):

$$\eta_{ir} = 1 + \frac{\beta_i}{w_{ir}} \tag{5}$$

And the Marshallian (uncompensated) price elasticities of AIDS is as follows:

$$\varepsilon_{ir} = -\,\delta_{ij} + \frac{\gamma_{ij}}{w_{ijr}} - \frac{\beta_i}{w_{ir}}(\alpha_i + \sum_r \gamma_{rj} \ln p_r) \tag{6}$$

4.1 How we implemented the approach

We used Stata software for our statistical analysis. For estimating the LA-AIDS model, we used the available package for estimating nonlinear systems of equation (nlsur) and the function evaluator program (nlsuraids). The available function evaluator program is designed for estimating an AIDS model for four product categories/markets. This code needs to be revised for changes in the number of products. The help document for using this command is available through Stata manuals.[27]

In addition to revisions to the function evaluator program, the nlsur command is sensitive to any missing values in the list of variables included. The most common reason for missing values is aggregation of the product categories with missing values.

27 Retrieved from: https://www.stata.com/manuals13/rnlsur.pdf

4.2 Data required for an LA-AIDS model

To estimate the LA-AIDS model, we required households' total expenditure data on the products that are subject to the study, the price of the products and the share of each product from the total expenditure.

The data available in the HES provides information on the annualised expenditure on products – this is variable 'amount'. This provides information about the required expenditure figures. Prices of the products, however, are not available in the HES. Therefore, we derive the pricing data separately from the data that Statistics NZ collects for the CPI and merged that with the HES data.

To derive information about the regions and merged the two datasets (HES and pricing) with the (within-class) product (HEC (Household Expenditure Categories)) codes, months and regions.

Table 1 New Zealand Household Expenditure Categories – an example

01	**Food**	**Group**
01.1	**Fruit and vegetables**	**Subgroup**
01.1.01	**Fruit**	Class
01.1.01.1	**Citrus fruit (fresh or chilled)**	within Class
01.1.01.1.0	Citrus fruit (fresh or chilled)	
01.1.01.1.0.01	Oranges (fresh or chilled)	
01.1.01.1.0.02	Lemons (fresh or chilled)	
01.1.01.1.0.03	Mandarins, clementines (fresh or chilled)	
01.1.01.1.0.04	Grapefruit, goldfruit (fresh or chilled)	
01.1.01.1.0.05	Tangelos, tangerines (fresh or chilled)	
01.1.01.1.0.99	Citrus fruit (fresh or chilled) nec	
01.1.01.2	**Bananas (fresh or chilled)**	within Class
01.1.01.2.0	Bananas (fresh or chilled)	
01.1.01.2.0.01	Bananas (fresh or chilled)	
01.1.01.3	**Apples and pears (fresh or chilled)**	within Class
01.1.01.3.0	Apples and pears (fresh or chilled)	

Source: Stats NZ

Details on the datasets that we used are provided in Section 4.4 and our solution for data issues in Section 4.5.

4.3 How we selected the categories included in our model

Ideally, competition or other policy analyses should be conducted at a 'market' level, as opposed to an 'industry' or 'expenditure class' level. The former refers to 'the set of products that impose constraints on each other's pricing or other dimensions of competition (quality, service, innovation)'.[28] Importantly, transport costs or other (e.g. perishability/storage or informational) constraints can mean that markets are often local/geographical. Thus, any given industry, which describes a range of similar activities, might comprise several different (e.g. geographical) markets.

[28] Davis, P. and E. Garcés, 2010, *Quantitative Techniques for Competition and Antitrust Analysis*, Princeton University Press, p. 162.

Furthermore, a given industry might not encompass the full range of products that impose constraints on its pricing – such as substitute goods produced by different industries. Likewise, an expenditure class might simultaneously relate to a number of markets, and not encompass the required range of alternatives for a proper market assessment.

So, for example, the liquid fuels industry might be thought to represent the market for liquid fuels. But the wholesale market for such fuels is defined by geographical constraints such as ownership and control of refinery access, shipping and/or fuel storage facilities. Likewise, the retail market for liquid fuels is more likely to hinge on the location of petrol stations relative to population centres and transport routes. Hence, any demand study looking just at the 'fuel industry' could confuse industry and market.[29]

Moreover, the market for liquid fuels – meaning any given local market for such fuels – would also need to consider the prices and qualities of products or services that materially constrain fuel prices (e.g. access to public transport). A focus just on liquid fuel expenditures, even if at a localised level, might also inadequately define the relevant market.

The challenge for the Project was to try to identify classes of expenditure available in administrative data sources:

- For which sufficiently granular/sub-national prices could be sourced from other administrative datasets; and
- In respect of which markets could be taken to correspond to collections of sub-national expenditure classes.

An important rationale for seeking sub-national markets (rather than identifying goods or services for which national markets might reasonably exist) is that this provides an additional source of data variation with which to enable estimation. If we restricted ourselves to using national price and expenditure data for a small set of expenditure classes, this would naturally limit the number of data points we have to use, and the amount of variation in those data.

Our strategy was to focus on a subset of high-level household expenditures of the sort that households might budget for as distinct categories, which also shared at least some of the above attributes. That then enabled us to estimate demand parameters relating to how households substitute across those broad expenditure classes – e.g. if the price of one broad expenditure class rose, what impact does that have on expenditures in some other high-level class. Opting for more granular expenditure categories could possibly have made it more difficult to generate significant estimates of price elasticities.

The following table summarises the markets we chose to include in the Project.

[29] For a comprehensive assessment of the New Zealand fuel market, see Cognitus Economic Insight, NZIER, and Grant Thornton, 2017, *New Zealand Fuel Market Financial Performance Study*, report prepared for the New Zealand Ministry of Business, Innovation and Employment, May.

Table 2 Markets included in the analysis

Market	Nature	Include with
Electricity – 'regional' by virtue of network constraints.	Top-level expenditure, relatively homogeneous.	Other top-level expenditures, e.g. housing, food, etc.
Motor fuels – 'regional' by virtue of distribution constraints (e.g. terminals).	Top-level expenditure, differentiated (e.g. spatially) homogeneous, observable input price.	Other top-level expenditures, e.g. housing, food, etc.
'Pleasure purchases' – tobacco, alcohol, junk food, confectionary, fizzy drinks, etc. (likely highly 'localised' by virtue of convenience/ accessibility).	Bottom-level expenditure, highly differentiated, mainly unobservable input prices.	Broader higher-level purchases, e.g. sub-set of food, which is chosen alongside housing, power, motor fuels, etc.

Source: NZIER and Cognitus Economic Insight

We assumed a household would allocate its budget across broad expenditure categories such as these, and that a price increase in one might induce changes in budget allocations to the others. In doing so we treat 'extensive margin' choices such as what household appliances to install, and where to live/work and what private vehicles to own, as given over households' decision-making time frames (we limit the analysis to households' 'intensive margin' choices).

In all three markets we can expect prices and expenditures to be regional or local, instead of national, thus providing the added degree of data variation that we felt important for successful estimation. A further rationale for focusing on these markets is their policy salience – the prices of key household expenditures such as electricity and motor fuels are often the focus of public and regulatory scrutiny. Similarly, the taxation of pleasure items (i.e. 'sin taxes' on tobacco, alcohol and soft drinks) is also an increasingly important focus of policy.

4.4 Data sources

We used the following datasets to estimate own-price and cross-price elasticities for major market groups in New Zealand: HES 2006/07; 2009/10; 2012/2013; 2015/16, and CPI pricing data from 2007; 2010; 2013 and 2016.

The HES data (extracted from the IDI) used in this analysis was:

Table 3 IDI data sources

Database	Table
IDI_Clean_20190420	hes_clean.hes_expend
IDI_Clean_20190420	hes_clean.hes_household
IDI_Adhoc database	clean_read_HES.hes_household_1516
IDI_Adhoc database	clean_read_HES.hes_expendire_1516

Source: Statistics NZ

The NZHEC categories that we considered for each market are shown in Table 4.

Table 4 New Zealand HEC used for each market

Market	NZHEC category
Food	01 (food)
Electricity	04.5.01 (electricity)
Accommodation	04.1.01; 04.1.01.1; 04.2.01 (actual rental for housing; purchase of housing)
Petrol	07.2.02 (petrol)
Alcohol	02.1 (alcoholic beverages)
Chocolate	01.3.05 (confectionary, nuts and snacks)
Cigarette	02.2 (cigarette and tobacco)

Source: Statistics NZ

4.4.1 Household Economic Survey

The HES information is collected every third year. The target population is the usually resident population aged 15 years and over, living in private dwellings. Data are collected using a household demographic questionnaire and an expenditure questionnaire that records larger purchases and regular payments made by a household over the previous 12-month period. Each eligible person in participating households is also asked to complete an expenditure diary recording all daily spending over a period of two weeks.

Each HES is carried out over a full 12-month period. The 2006/07 HES included 2,902 households, the 2009/10 HES included 3,126 households, the 2012/13 HES included 3,003 and 2015/16 HES included 3,499 observations. Data from the two surveys were aggregated and used to develop PE values for New Zealand.

4.4.2 Pricing data

The data we used was the average price data from monthly collected prices – includes prices on food, non-food supermarket items, fuel, international flights, during the months for the HES dataset.

Table 5 Pricing data

Product code	Region code	Time	Price
011011001	1	2006q1	$p1
011011001	2	2006q1	$p2
011011001	2	2006q2	$p3

Source: NZIER; Statistics NZ

The pricing data is available for 501 product categories. Except for the ‘Sales, trade-ins and refunds’ NZHES category, pricing data is available for all other products to the extent that with different aggregating strategies researchers have enough information on prices.

We derived pricing data for 149 food categories, and one for each of the accommodation, electricity and petrol categories. For the other market, we have information on 11 Alcohol products, 2 cigarette categories and 10 chocolate categories.

4.5 Data issues and how we resolved them

When aggregating to market levels, there are often missing values for a number of markets. This reduces the number of households with available information on all relevant markets significantly. For this issue, we use the Heckman correction method to overcome the potential selection bias issue. While we expect that the Heckman correction method will overcome the potential selection bias, a future study might use other methods to address the selection bias and compare the outcomes with our findings.

The format of the New Zealand HEC was not consistent between the pricing data and the HES data. We fixed this issue by redefining the format of the reported categories and then assuring a consistent merging of the observations.

In the pricing data, the unit of the items is important for descriptive analysis. Some products are measured in kilograms, some in packages and some in duration of consumption (e.g. month). In the data we used, the price of food products is per 1 kg, electricity is per month of consumption, chocolate is per 250 grams, cigarettes is per packet of 25, and the price of alcoholic drinks are in a package of 6, or in millilitre units. This causes further complications for finding average prices.

When data was not available for the prices of a within-class product at a time (and in a region), we used the average price at the class levels and if we still did not have enough information on prices we used the average of subgroup level prices. If we had prices data for a region, e.g. in Napier and Nelson, we replaced prices with the average price of the product category at time t.

In the HES data, the categories with the lowest incidence of zero consumption were: Food; Alcoholic beverages, tobacco and illicit drugs; and Housing and household utilities. The incidence of zero expenditure was highest for Sales, trade-ins and refunds, Other expenditure (such as interest payments), Miscellaneous goods and services, and Clothing and footwear.

After cleansing the pricing data, and merging with the HES data, we had 410 detailed (within class) product categories in HES under the food category with no pricing information. When we replaced the missing price information with the average sub-category (class) price levels, the number of missing categories decreased to 8.

There are inconsistencies between HES and CPI in the categories used for the regions' variable. To solve this issue, we aggregated the geographic units to the regional levels.

The 2015/2016 HES data is located in a different database (IDI_Adhoc database) from the rest of the HES data. The name of the variables and the format of them (string versus numeric) are different between the datasets and need to be resolved in the process of merging the datasets.[30]

[30] In addition to these issues, we had a few simple but time consuming issues with the Stata software package. To use the Stata commands, we needed to reshape the data from long to wide. That is associated with a wide range of considerations in case of any inconsistencies across the merged datasets. Also, the Stata code needed to be revised when the number of products in the analysis changed.

4.6 Heckman selection procedure

For some households the expenditure on some items are equal to zero during the data collection period (2 weeks). If this lack of information occurs systematically (i.e. non-randomly) that would lead to biased estimation of the AIDS parameters. To overcome this issue, we used the Heckman's two-step (Heckit) method.

In a first step, we estimate a probit model where the dependent variable is a binary dummy equal to one when household has reported spending on an item (and zero otherwise). The explanatory variables included a range of household features, including the composition of the household, the size of the household, the region dummies, the household's total expenditure, the household tenure and the year dummies.

In the second step, we added the inverse Mills' ratios estimated from the first step to the AIDS equation (1).

4.7 Summary of the data we used

For the expenditure data, we used the annualised expenditure on each item, available in HES dataset. Descriptive statistics are presented in Table 6 (over the page).

For 2006q1-2016q2, average spending on alcohol drinks was $42.9 a week and the spending on cigarettes and chocolate was $42.4 and $18.9, respectively. In the same period, the average price of alcoholic drinks, cigarette sand chocolate was $15.5, $31.2 and $2.7, respectively.

The average price of accommodation for 2006q1-2016q2 is $346, electricity $138 (per household per month), petrol 1.84 per litre and food 5.28 per unit (kilo). In the same period, the average expenditure on accommodation, electricity, food and petrol were $215, $38, $218 and $55.6, respectively.

Table 6 Demographic characteristics of households

Households	Number	Proportion
2006/2007	2,902	0.23
2009/2010	3,126	0.25
2012/2013	3,003	0.24
2015/2016	3,499	0.28
Total population	12,530	1.00
Household by region		
Rest of North Island	327	2.61
Auckland	2,955	23.58
Hamilton	903	7.20
Bay of Plenty	750	6.00
Napier-Hastings	564	4.47
New Plymouth	372	2.97
Palmerston North	675	5.40
Wellington	1935	15.42
Canterbury	2,100	16.74
Dunedin	864	6.90
Rest of South Island	420	3.36
Nelson	390	3.09
Household by composition		
Couple only	3,675	29.34
Couple with children	3501	27.93
One parent with children	1137	9.09
One-person household	3519	28.08
Others	627	5.01
Household by size		
1 person	2904	6.27
2 persons	1635	1.80
3 persons	1998	0.57
4 persons	1848	0.27
5 persons or more	1152	0.27

Source: HES 2006/2007; 2009/2010; 2012/2013; 2015/2016.

5 Estimation results

5.1 LA-AIDS model parameter estimates

In our estimation of equation 1, we control for the impact of household income levels, household composition dummies, and region dummies. Also, the inverse Mills' ratios were included as an independent variable in the demand equation. We present the estimation results for the accommodation, electricity, food and petrol market in Table 7 and for the pleasure purchases in Table 8.

Table 7 Estimation results for the accommodation, electricity, food and petrol markets

Parameter	Coefficient	S.E.	95% confidence interval	
a1	-0.071	0.054	-0.177	0.035
a2	0.309***	0.026	0.257	0.360
a3	0.752***	0.045	0.664	0.838
b1	0.086***	0.006	0.074	0.097
b2	-0.058***	0.002	-0.061	-0.055
b3	0.006	0.005	-0.004	0.017
g11	0.114***	0.014	0.087	0.141
g12	-0.023***	0.004	-0.031	-0.015
g13	-0.072***	0.012	-0.095	-0.048
g22	-0.038***	0.010	-0.057	-0.019
g23	-0.027***	0.005	-0.038	-0.017
g33	0.116***	0.013	0.091	0.141
Controls	yes			

Source: NZIER; * p<0.1, ** p<0.05, *** p<0.01; reported upper and lower estimates are based on 95% confidence level.

Table 8 Estimation results for the alcohol, chocolate and cigarette markets

Parameter	Coefficient	S.E.	95% confidence interval	
a1	0.373***	0.040	0.300	0.450
a2	0.260***	0.045	0.170	0.348
b1	0.031**	0.009	0.013	0.050
b2	-0.070***	0.006	-0.082	-0.058
g11	0.006	0.028	-0.048	0.060
g12	0.007	0.019	-0.031	-0.045
g22	0.015	0.022	-0.028	-0.058
Controls	yes			

Source: NZIER; * p<0.1, ** p<0.05, *** p<0.01; reported upper and lower estimates are based on 95% confidence level.

5.2 Estimated income and price elasticities

For each market elasticity, we calculated the results across four regions:

- New Zealand (NZ)
- Large urban areas (LUs): consisting of Auckland and Wellington
- Medium urban areas (MUs): consisting of Christchurch, Dunedin, and Hamilton)
- Small urban areas (SUs): rest of New Zealand.

The elasticities with statistical significance at 95% confidence level are bolded.

Indicative own-price elasticities and cross-price elasticities are presented in Table 9 (over the page).

According to the own-price elasticities, higher prices of accommodation does not affect consumption of accommodation in the LUs and MUs significantly, and in SUs demand is inelastic.

For electricity, own-price elasticities suggest an elastic demand that decreases significantly as a result of an increase in electricity prices. The own-price elasticities for food products are insignificant, except for SUs where households decrease their consumption of food significantly when the price of food increases. An increase in the price of petrol is associated with significant decreases in its demand, except for MUs where demand does not change significantly.

In terms of cross-product elasticities, a positive elasticity indicates substitutability and a negative elasticity suggests complementarity between two markets. Our findings suggest that:

- Accommodation and food are substitutable in SUs
- Higher cost of accommodation is associated with lower petrol consumption (i.e. petrol and accommodation are complementary products), except for SUs where accommodation and petrol are substitutable.
- Electricity and accommodation are complementary in LUs and substitutable in SUs
- Electricity and petrol are significantly substitutable in all urban areas.

Table 9 Estimated own and cross product elasticities

The elasticities with statistical significance at 95% confidence level are in bold.

	Urban size	(1) Accommodation	(2) Electricity	(3) Food	(4) Petrol
Accommodation	NZ	**0.14**	**-0.11**	**-0.88**	**-0.14**
	Large	2.12	-0.15	**-2.63**	**-0.35**
	Medium	-0.19	**-0.11**	**-0.25**	**-0.44**
	Small	**-0.28**	**0.21**	**0.99**	**0.58**
Electricity	NZ	**-5.50**	**-4.12**	**-3.41**	**11.41**
	Large	**-4.77**	**-6.10**	**-3.41**	**13.31**
	Medium	**-5.75**	**-3.13**	**-6.92**	**10.29**
	Small	**-2.06**	**-4.00**	**-6.88**	**11.08**
Food	NZ	**-0.33**	**-0.05**	-0.59	**-0.03**
	Large	**-0.84**	**-0.08**	-0.19	**0.11**
	Medium	**-0.14**	**-0.02**	-0.68	**-0.16**
	Small	**0.26**	**-0.12**	**-1.01**	**-0.15**
Petrol	NZ	**-0.72**	**1.86**	**-0.33**	**-1.83**
	Large	**-0.82**	**2.09**	**0.47**	**-2.69**
	Medium	**-1.20**	**1.71**	**-1.03**	-0.54
	Small	**0.30**	**1.89**	**-1.10**	**-2.20**

Source: NZIER

For the alcohol, chocolate and cigarette markets, the own- and cross-product elasticities are shown in Table 10 (over the page).

Accordingly, a 1% higher prices of the product leads to a 1.02% decrease in consumption of alcohol and no significant change in the consumption of chocolate and cigarettes.

The cross-product elasticities suggest less consumption of chocolate and cigarettes with increases in the price of alcohol. The impacts are not material such that a 10% increase in alcohol prices decreases chocolate consumption by 0.8% and the consumption of cigarettes by 1%.

A 10% increase in price of cigarettes leads to 1.3% decrease in the consumption of alcohol and a 6.3% decrease in consumption of chocolate.

Table 10 Estimated own and cross product elasticities

	(1) Alcohol	(2) Chocolate	(3) Cigarette
Alcohol	**-1.02**	**0.15**	**-0.13**
Chocolate	**-0.08**	-0.45	**-0.63**
Cigarette	**-0.10**	**0.01**	-0.93

Source: NZIER

Table 11 shows indicative estimated expenditure elasticities. Accordingly,

- A 1% increase in price of accommodation leads to a 2.04% increase in households' spending on accommodation.
- The spending of households on electricity does not change significantly if the price of electricity increases.
- As a result of a 1% increase in the price of food products, households' expenditure on food products increases by 1.02%.
- A change in the price of petrol does not change households' expenditure significantly.
- A 1% increase in the price of alcohol is associated with a 1.14% increase in households' expenditure.
- A 1% increase in the price of chocolate does not change households' expenditure significantly.
- A1% increase in the price of cigarettes increases households' expenditure significantly by 1.16%.

Accordingly, accommodation, alcohol and cigarette markets are categorised as luxury markets for New Zealanders.

Table 11 Estimated expenditure elasticities

Market	NZ	Large	Medium	Small
Accommodation	**2.04**	**2.12**	**1.89**	**1.77**
Electricity	-5.75	-5.52	-5.47	-5.82
Food	**1.02**	**0.98**	**1.05**	**1.11**
Petrol	0.38	0.40	0.45	0.36
Alcohol	**1.14**			
Chocolate	-0.23			
Cigarette	**1.16**			

Source: NZIER

6 Conclusions and recommendations

We studied the markets for accommodation, electricity, motor fuels and pleasure purchases. We chose these markets partly because of their topicality, but also because of the granular prices from administrative datasets could be matched to sub-national expenditure classes.

6.1 Own-price elasticities

Our results indicatively suggest that an increase in own price leads to:

- No change in the demand for accommodation
- A significant decrease in the demand for electricity
- A decrease in the demand for food in small urban areas
- Significant decreases in demand for petrol, except for medium size urban areas where demand does not change significantly.

Own-price elasticities for the pleasure purchases suggest that a 1% increase in own price leads to a 1.02% decrease in consumption of alcohol, but no significant change in the consumption of chocolate and cigarettes.

In terms of cross-price elasticities, our results indicatively suggest that a 10% increase in the price of cigarettes leads to a 1.3% decrease in the consumption of alcohol and a 6.3% decrease in the consumption of chocolate.

6.2 Statistics NZ provides enough data for market studies of demand

This is the first study undertaken by researchers in New Zealand with access to geographically granular pricing data (at regional levels).

6.3 The AIDS model is an appropriate modelling framework for studies of demand

While this is an exploratory study, we find most of our results are sensible and we recommend that the AIDS modelling approach be considered for future studies of demand. We however encourage further exploration of alternative AIDS methods, such as QUAIDS[31], to compare the results and understand the reasons for any differences.

6.4 Recommendations regarding data collection and availability

The available HES data tables are in different databases and the name of the variables change across different waves of data. We suggest providing a comprehensive guideline on the HES data and that these differences are described more clearly.

31 Banks, J., Blundell, R., & Lewbel, A. (1997). Quadratic Engel curves and consumer demand. Review of Economics and statistics, 79(4), 527-539.

Pricing data is now available in the IDI provided by Statistics NZ.[32] The coding of the product categories between the pricing data and the HES data are not consistent and that can lead to difficulties in merging the two datasets.

6.5 Recommendations for future research

IDI provides access to a wide range of relevant information that could be used to address the potential identification issues involved in demand estimation, such as endogeneity. A future study could investigate the use of other available datasets in the IDI to address the identification issues.

We have tried addressing potential selection bias, by using a Heckit approach. While that provides satisfactory outcomes, we recommend further investigation by using other variables available from datasets in the IDI.

There is potential for measurement bias due to heterogeneity of products – i.e. products may be provided in different quantities and qualities in different locations. That may affect the sensitivity of consumers to a price change.

We have disaggregated our estimation to regional levels and compared the results between different regions. Our results suggest that consumers' sensitivity to price differs across regions. There may be the need for further disaggregation geographically or by product groups or the unit that the products are measured in. That will be a good topic for a future study to test on the differences in results.

Finally, a useful extension of this analysis could be to provide a comprehensive assessment tool, that can easily adjust the number of products included in the analysis and be applied to all the HES data after accounting for a wider range of control variables. We think that tool can provide useful insights for the analysis of markets in the future.

6.6 Conclusions

We have successfully used administrative data to estimate demand at a regional level using the AIDS model.

While not a straight-forward procedure, we have now established a procedure that can be applied to other produces where suitable data is available. The relevant computer code is now stored in Stats NZ's Datalab.

[32] Researchers needs to apply for accessing the data using Stats NZ IDI application process.