Product labelling regulatory review: supermarket competition cost-benefit analysis

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Abstract

The New Zealand supermarket sector is essentially a duopoly, with entry barriers hindering competition. Product labelling requirements may contribute to these barriers, because an entrant that relies on imported products must relabel or over-sticker its products to meet domestic labelling standards, which increases costs. In this paper, we analyse the welfare implications of changes to labelling regulations that mitigate this entry barrier. We use a multinomial discrete choice logit model in which households choose the local supermarket store that maximises their utility by considering prices and other store characteristics. We first solve a static competition model of profit-maximising incumbent supermarkets in each local market in the country. We then re-solve the model adding an entrant 'hard-discounter' that offers low prices and a narrow product range, and calculate the consumer surplus and profit impacts of entry. Using a set of profit-based entry rules, we simulate 10 years of entry decisions across all markets in the country with and without a regulatory intervention that lowers the entrant's cost per item, enabling it to open more stores sooner. We find such a regulatory intervention could facilitate the entrant opening an additional 11 stores in its first 10 years of operation, resulting in an increase in domestic social welfare of $166 million in net present value over 10 years. This result shows how reduced costs for a supermarket entrant could lead to increased competition in this sector and improved social welfare.

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1 Introduction and summary

As part of the product labelling review, the Ministry for Regulation undertook a cost-benefit analysis (CBA) of the impact of product labelling regulations on supermarket competition. Our analysis is motivated by a claim that changes to product labelling requirements may improve competition between supermarkets.

The New Zealand supermarket sector is currently characterised by a duopoly between Foodstuffs and Woolworths. Product labelling requirements may be contributing to the barriers to a third player entering and competing with the incumbents. A new entrant that relied on imported products (such as its own private label brands, or from its own supply chains) would find the overseas labels do not comply with New Zealand standards. The entrant would therefore need to incur a cost to relabel or over-sticker its products to be able to sell them in New Zealand. Changes to labelling regulations may therefore reduce an entrant's costs, mitigating this entry barrier and allowing an entrant to more easily enter to compete with the incumbents.

A number of other barriers may be impeding entry into the supermarket sector, such as those identified by the Commerce Commission in its 2022 market study into the retail grocery sector (Commerce Commission, 2022). An implicit assumption in our CBA is that these barriers are lowered through other means, allowing a new supermarket chain to enter even without changes to product labelling regulation. We take this as the counterfactual scenario and compare it with a factual scenario in which a specific regulatory intervention in product labelling lowers the entrant's costs per product, and calculate the net present value of the benefit to New Zealand arising from this regulatory change.

We model supermarket competition similarly to other industrial organisation economics literature. Our model was completed under very tight deadlines, and, while it is analytically rigorous, it makes a number of assumptions for simplicity and tractability.

We first split the country geographically into 200 markets in which we assume supermarkets compete, and identify the current stores operating in each. For example, we model a market around the Auckland Central Business District, capturing Ponsonby, Grey Lynn, Newmarket, and surrounding areas. There are 15 competing stores in this market, covering the Four Square, New World, and Woolworths brands. We assume competition within each market occurs independently of competition in others. This approach is motivated by the Commerce Commission's finding that consumers do not usually travel long distances to buy their groceries, but simplifies real world dynamics.

We then model households as maximising their utility, assuming each household chooses just one store to shop at by considering average prices and other store characteristics. At their chosen store, households decide what quantity to buy based on price.

We next model competition in each market in a base case with no entrant. The incumbents in each of these markets may own multiple stores under their current brands: Foodstuffs owns New World, Pak'nSave, and Four Square; and Woolworths owns Woolworths, SuperValue, and FreshChoice. Each duopolist incumbent chooses the prices at all of its stores in a given market to maximise its profits. For simplicity, we exclude other grocery providers such as Costco, The Warehouse, and specialist supermarkets. However, we capture competition from such providers through an 'outside option', wherein consumers shop somewhere other than a Foodstuffs or Woolworths store. We calibrate the model with data including household supermarket expenditure, incumbent costs, store assortment (stock keeping units, SKUs), and store customer experience levels (amenities, service quality, etc), and solve the model for optimal prices, quantities, incumbent profit, and consumer utility.

We then consider the case where an entrant has entered each market. We model our entrant as a 'hard discounter', which is a format that focuses on offering low prices, a narrow product range (limited SKUs), and other low-cost strategies such as a minimalist store experience. Our model assumes the hard discounter entrant sets a price at a fixed percentage below that of the incumbents in the base case and offers a limited SKU range. It further assumes that only a fraction of households consider whether to shop at the entrant's stores because not all households may know about them and the hard discounter format will not appeal to all types of shoppers. We similarly solve this model of competition between the three firms for optimal incumbent prices, incumbent and entrant quantities and profit, and consumer utility in each market.

By comparing the outcomes of these two static competition models, we estimate how firm profits and consumer surplus in each market would be affected if the entrant were to enter.

We next predict which markets the entrant will enter and when under two different scenarios: the status quo (counterfactual) and a scenario with regulatory relief from product relabelling costs (factual). We model the regulatory relief by assuming it decreases the average cost per item to the entrant by 20c. We assume regulatory relief does not affect incumbent costs because they already have sources of compliantly labelled products. In both scenarios, we assume the entrant will prioritise entering markets where it can more quickly recoup the fixed costs of its entry, and will enter a new market only after operating profits (revenue less variable costs and annual fixed costs) from its existing stores exceed an assumed percentage of the total fixed costs of entry it has incurred.

Using these entry rules, we simulate 10 years of entry decisions across all markets in the country in the factual and counterfactual scenarios. In both scenarios, the entrant tends to enter the more urban markets first, because these have a greater population density and give it greater ability to generate scale to recover its entry costs.

A market the entrant has not yet entered yields consumer surplus and profit outcomes each month from the static base case described above. Once the entrant enters a new market, we assume its impact on consumer surplus, its own revenue and variable costs, and incumbent profits scale linearly over time to capture the time it takes to build a reputation and gain market share. However, the entrant incurs full fixed costs from the month of entry. Once the new entrant store reaches full scale, the market yields the outcomes from the static entry case described above each month.

For each point in time and in each of the factual and counterfactual scenarios, we add up consumer surplus and incumbent and entrant profits across markets in the country to give national pathways over time for these values in the factual and counterfactual scenarios. We discount these back to present day values using an 8% discount rate. We take the difference between these in the factual and counterfactual scenarios as the effect of the regulatory intervention. The net benefit to New Zealand of the regulatory intervention is the sum of the impacts on consumer surplus, Foodstuffs's profits, and the entrant's profits. Effects on Woolworths's profits are not included in this calculation because it is foreign-owned.

The direct effect of the regulatory intervention is to lower the cost per item faced by the entrant. This enables it to accumulate profit more quickly and thus reach more markets in a shorter period of time. When it enters a market, consumers in that market benefit because they have an additional choice of supermarket where they can shop, the new store has lower prices, and competition from the entrant causes the incumbents to also lower their prices. Having more stores enables the entrant to accumulate profit faster, but decreases incumbent profits in the markets where it enters.

In the simulation of entry that uses our best estimates of the model parameters, we find the regulatory intervention causes the entrant to open an additional 11 stores over 10 years (relative to the counterfactual). It thus increases the net present value (NPV) of consumer surplus over this period by $174 million. The regulatory intervention increases the number of households in markets served by the entrant by 366,000 by the end of 10 years; by this date, each household in a market served by the entrant is benefiting by an average of $182 per annum.

We find also the entrant increases its profit by $21 million in NPV. However, the NPV of Foodstuffs's profits decreases by $29 million and the NPV of Woolworths's profits decreases by $33 million.

Overall, the sum of consumer surplus, profit gains to the entrant, and profit losses to Foodstuffs result in a net benefit to New Zealand over 10 years of $166 million in NPV. If the change in Woolworths's profits were also included in this figure, the NPV of the benefit over 10 years would be $133 million.

Because many of the model parameters are uncertain, we also run a collection of simulations where we randomly vary each parameter within the plausible range. This results in a 90 percent confidence interval for the NPV of consumer surplus of $0 to $424 million and a 90 percent confidence interval for overall net benefit of $0 million to $404 million. The $0 arises for the lower bound because for some random simulations the entrant does not enter any markets in either the factual or counterfactual. As an example, this occurs in a simulation when the entrant has a large price discount relative to the incumbent, which makes it difficult for the entrant to earn sufficient profits to recover its entry costs.

Our analysis is based on a stylised model that abstracts from real-world complexities and makes a number of simplifying assumptions. For example, it assumes that supermarkets do not compete on non-price dimensions, and that the incumbents will not respond to entry through aspects such as brand repositioning, product quality, amenities, and service levels. Nor will any incumbent stores exit. It also makes a number of simplifying assumptions in respect of entry, such as that the entrant enters with at most one store in a given market. These assumptions are necessary for analytical tractability, but do not detract from the model's rigour and transparency. In taking the results of this model as the net benefit to New Zealand, we assume the regulatory change is able to be done in a way that does not increase the risk or cost to consumers from unfamiliar labelling conventions. If this were not true, the negative impact on consumers should be subtracted from the net benefit we estimate. However, we incorporate other conservative assumptions into our analysis that likely offset against this.

Our overall net benefit result, of $166 million in NPV over 10 years, should be considered in light of groceries being a significant category of expenditure for all New Zealanders. In the year to June 2025, households spent over $27 billion at supermarket and grocery stores.[1] The Commerce Commission also found in its 2022 grocery market study that competition was not working well in grocery markets, with the incumbents earning excess returns of approximately $430 million per year (Commerce Commission, 2022, paragraph 3.54). When considered relative to the size of the industry, and the current level of competition, we would expect material net benefits from entry and thus from a regulatory change that facilitated a greater level of entry.

The remainder of this report is structured as follows. Section 2 describes the product labelling regulatory intervention and how we implement it in our CBA. Sections 3 and 4 explain the set-up and calibration respectively of the static model, while Section 5 shows how we solve the model. Section 6 presents the results of our static model. Section 7 then lays out the set-up of the dynamic model, where we simulate entry decisions in the factual and counterfactual, and Section 8 sets out the results of the dynamic model. Finally, Section 9 summarises our main results and offers cautions for their interpretation.

2 Regulatory intervention

This section describes the regulatory change on which we conduct this CBA.

As part of the Ministry for Regulation's review of product labelling, the Ministry has uncovered the claim that New Zealand product labelling regulation may be reducing the ability of new firms to enter the supermarket sector and provide increased competition to incumbents. The issue arises because products sold in supermarkets in New Zealand must be compliant with New Zealand labelling regulations. In food and beverages, these regulations are largely harmonised with Australia's regulations, but imports from other countries are not compliant.

[1] Statistics New Zealand, Retail Trade Survey: June 2025 quarter

One solution to this problem would be for an entrant to purchase products from suppliers that supply the incumbent supermarkets, where products are already labelled compliantly. However, the Commerce Commission in its grocery market study found a key barrier to entry was the lack of wholesale access to groceries, either from a range of suppliers or a grocery wholesaler (Commerce Commission, 2022, p.189). While the Commission has since introduced a wholesale access regime, it notes that this is not having a material impact at present (Commerce Commission, 2024a, p.125). The Commission also identified exclusive supply agreements (particularly in respect of private label products) as being prevalent, which may limit the ability of suppliers to supply an entrant supermarket (Commerce Commission, 2024a, pp.126-127).

An alternative would be for an entrant to source products from elsewhere, which likely means outside New Zealand and Australia. Products imported from jurisdictions such as the EU, UK, or US would need to be relabelled or over-labelled with compliant labels before they could be sold in New Zealand. The additional cost of this would increase the entrant's cost per item, reducing its ability to make a competitive return on its investment, thereby potentially acting as a barrier to entry.

The regulatory change we analyse in this CBA is conceptualised as a change that removes this need for relabelling. We are not specific about how this is achieved, but we assume it does not prevent consumers accessing the information they need about the products, and so does not impose additional cost or risk on consumers. If this assumption does not hold, the cost imposed on consumers should be subtracted from the net benefit we estimate.

We model the change as decreasing the average cost per item incurred by an entrant to the supermarket sector by 20 cents. This is based on information gathered in the course of the Ministry's product labelling review that claims the cost of relabelling is between 20 and 40 cents per item. On the basis that not all items sold would need to be relabelled, we choose the lower end of this range.

We assume the regulatory change affects the costs of a potential entrant, but does not affect the costs of the incumbents. The rationale is that the incumbents already have access to compliantly labelled products, either because they source from within Australia or New Zealand, or because they have the scale to negotiate with their international suppliers to have product lines produced that are compliant with New Zealand regulation.

In this CBA, we estimate the extent to which this reduction in costs makes the New Zealand supermarket sector more profitable for an entrant, and thus encourages it to enter the country and open more stores more quickly, with consequent impacts on the profits of the incumbents and consumer welfare.

3 Static model set-up

This section describes the set-up of the static model that estimates competitive outcomes in each market in the country and how these would change if an entrant were to open a store there.

We model households as choosing which store to shop at to maximise their utility, which depends on average prices and other store characteristics. Households choose from stores within their geographic market. At their chosen store, they decide the quantity of groceries to buy based on price.

For each market, we model a base case with no entrant in which the incumbent stores compete with each other through price. We also model a case where an entrant enters each market offering an exogenously lower price. By comparing the outcomes of these base case and entry case static competition models, we estimate how firm profits and consumer surplus in each market would be affected if the entrant were to enter.

3.1 Geographic markets in which supermarkets compete

We assume supermarkets compete within geographically defined markets. Households that live in a market shop within that market, and supermarkets located in a market make profit-maximising decisions by considering only households and other supermarkets in the same market.

We make this assumption for analytical tractability. It is motivated by the Commerce Commission's finding that most households do not travel long distances to do their grocery shopping (Commerce Commission, 2022, at paragraph 4.22), but it simplifies real-world dynamics in a number of ways. For instance, it assumes away the ability of households that live in one market to shop in another, which would make a supermarket's optimal pricing decisions in one market dependent on pricing decisions in nearby markets. It means firm pricing decisions are made independently in each market. This precludes, for instance, incumbents increasing prices in markets an entrant has not entered to cross-subsidise their stores in markets where they face strong competition from the entrant.

We define markets based on New Zealand's Statistical Area 2 (SA2) units from 2023. SA2s with zero land area are excluded from our analysis. Many SA2s are very small and it would be implausible to expect all households that live in an SA2 to do their grocery shopping in the same SA2, partly because many SA2s do not contain a supermarket. We therefore aggregate SA2s together to define mutually exclusive markets in which supermarkets are assumed to compete.

Based on centroids for each SA2, we use population-weighted k-means clustering to aggregate markets (see, e.g., Ikotun et al., 2023). This approach sets k markets, and allocates SA2s to a market to minimise the sum of squared distances between market centroids and SA2 centroids, weighted by population (to ensure market centroids are pulled towards the area of highest population density). Our measure of population is the usually resident population from Statistics New Zealand's 2023 Census.

We compared the output of this approach using $k = 190, 200, \text{or } 210$ markets,[2] and found 200 produced the best trade-off between population balance (ensuring markets have similar populations) and geographic compactness of the market, using the equation:

$$\text{Score} = 0.6CV_{pop} + 0.4\frac{\bar{D}}{10\text{km}} \tag{1}$$

where CV_{pop} is the coefficient of variation (ratio of standard deviation to the mean) for population and $\bar{D}$ is the mean straight-line distance from SA2 centroids to the centroid of the market. A lower coefficient of variation means that population is more evenly distributed across markets, while a smaller distance means that markets are more geographically tight. A lower score therefore yields a better trade-off between population balance and geographic compactness. We consider that slightly more weight should be given to population balance, given that uneven populations are likely to create more material distortions to the analysis, and therefore apply the weighting of 0.6 to population balance and 0.4 to geographic compactness.

Geographic compactness is important given the Commerce Commission's finding that consumers are generally willing to travel limited distances to visit a supermarket. We scale geographic compactness by dividing by 10km, reflecting the Commerce Commission's use of 5-15km to estimate the size of geographic markets (Commerce Commission, 2022, at paragraphs 4.125 and 4.126). For computational simplicity, we use straight-line distance rather than travel time. This is likely to be a good approximation in a lot of situations, but will be a poorer approximation where geographical features such as rivers or steep slopes make areas that are close to each other slow to travel between.

The above approach gives us 200 mutually exclusive markets across the country. This approach is necessarily a simplification: our markets are not based on actual data that link

[2] We test variations around 200 markets based on Coriolis et al., 2022, who similarly split the country into approximately 200 markets to analyse the costs and benefits of supermarket divestment options.

where households live to which supermarkets they shop at. However, this approach does provide an analytically tractable way of defining the geographic scope of competing supermarkets.

Having determined these markets, we also determine their level of 'urbanness', using Statistics New Zealand's urban-rural classification system. Statistics New Zealand classifies each SA2 based on the population of the area it falls into as:

- Major urban area: population greater than 100,000.
- Large urban area: population between 30,000 and 99,999.
- Medium urban area: population between 10,000 and 29,999.
- Small urban area: population between 1,000 and 9,999.
- Rural area: population less than 1,000.

We categorise each market based on the most urban of its constituent SA2s.

3.2 Incumbent supermarkets and their allocation to markets

The incumbents' stores we include in our model are those owned by Foodstuffs and Woolworths that were operating in November 2025. Our model allows each incumbent to own different supermarket brands. Foodstuffs owns the New World, Pak'nSave, and Four Square brands; and Woolworths owns the Woolworths, SuperValue, and FreshChoice brands.

Our data set contains 222 Four Square stores, 75 FreshChoice stores, 149 New World stores, 60 Pak'nSave stores, 4 SuperValue stores, and 187 Woolworths stores.

We do not explicitly capture supermarket sales by other retailers such as Costco and The Warehouse, or by smaller independent or specialist supermarkets. However, we do incorporate household substitution to these stores by modelling an outside option. That is, we assume that a certain percentage of households shop at the major supermarket chains, with the remainder shopping at alternative stores not explicitly modelled.

We combine information on the latitude and longitude of each incumbent supermarket taken from a combination of Google Maps and data provided by the Commerce Commission collected as part of its 2022 Grocery Market Study (Commerce Commission, 2022) and 2024 Annual Grocery Report (Commerce Commission, 2024a) with GIS data on SA2 boundaries to locate each supermarket in an SA2. We then attribute the supermarket to the geographical market to which its SA2 belongs.

Out of our 200 markets, 39 have no stores in them, 37 have only one store in them, and 21 have more than one store but only one incumbent in them. We omit these markets from the remainder of the analysis on the assumption they will not be worth entering for the entrant.

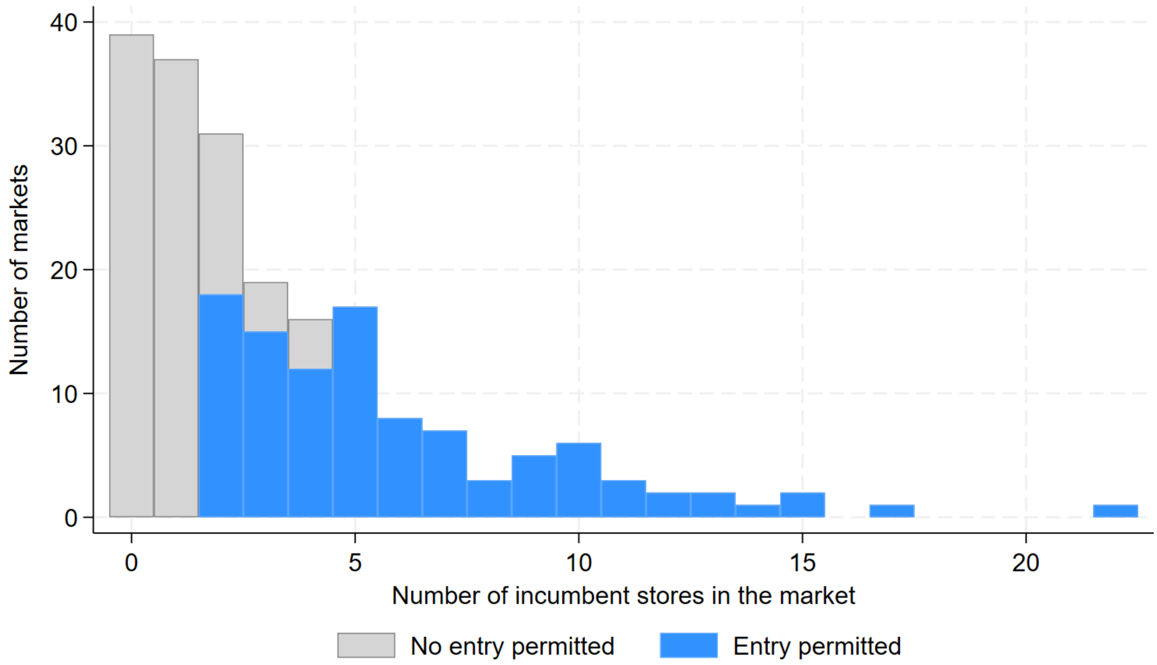
Figure 1 shows the distribution across markets of the number of incumbent stores, distinguishing between markets into which our model permits entry and markets into which our model does not permit entry. The highest number of stores in any market is 22.

3.3 Household types in each market

Each market is also characterised by the number of households of each type it contains.

We assume households differ only in terms of their income; those with different levels of income implicitly have different budget constraints, and have different parameters in their utility functions, which drive different shopping choices. This abstracts away from complications such as the number of individuals in the household and the household structure in the interests of data availability and relative analytical simplicity. It nonetheless captures a major reason households might spend different amounts on their groceries or choose different stores at which to shop.

Figure 1: Distribution of incumbent stores across markets that permit and do not permit entry



We group households into five income quintiles, $g = 1, ..., 5$. Within each income quintile and market, the total number of households is denoted M_g.

We choose five income groupings for three reasons:

1. The household expenditure survey (HES) data from which we source grocery expenditure data provides these data for each household income decile, allowing for tractable aggregation into quintiles.

2. Census income bands can be aggregated into groups that broadly mimic quintiles.

3. We require elasticities by income grouping, and the literature from which we draw calculates these for quintiles (Mhurchu et al., 2013).

We construct the number of households in each market and income quintile from 2023 Census data on the number of households in each income band and SA2. Within each SA2, we first aggregate Census income bands to approximate quintiles as follows:

1. Up to \$50,000 per year: 27 percent of all households.

2. \$50,000 to \$100,000 per year: 24 percent of all households.

3. \$100,000 to \$150,000 per year: 21 percent of all households.

4. \$150,000 to \$200,000 per year: 13 percent of all households.

5. Over \$200,000: 14 percent of all households.

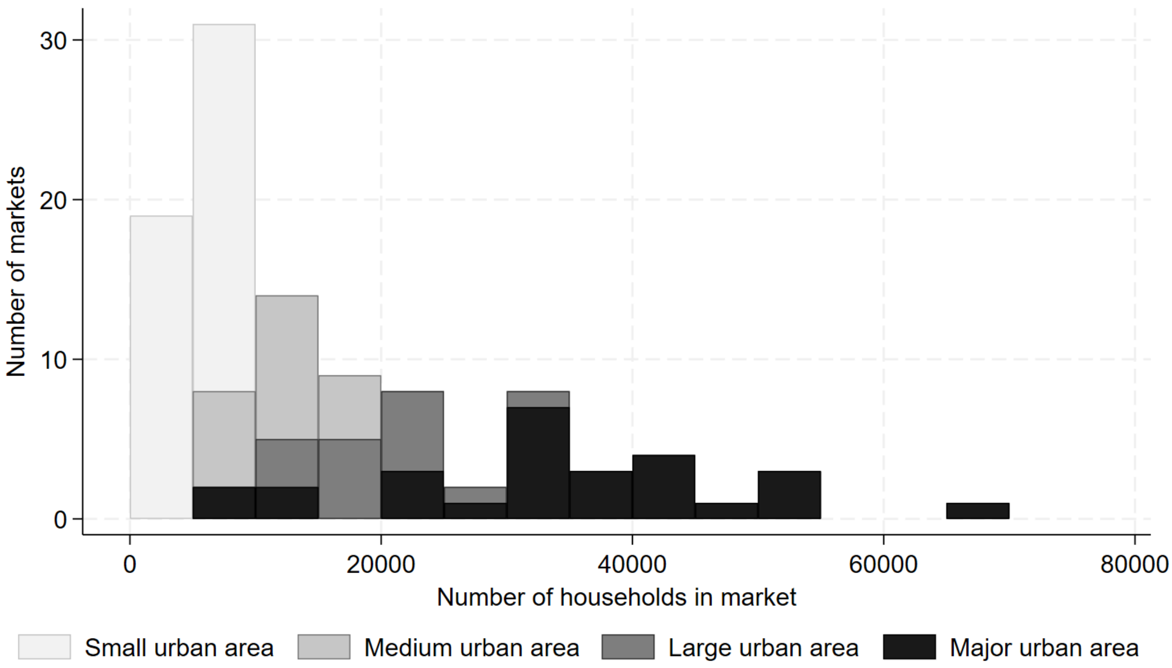
We then aggregate across SA2s in a market to yield the population (number of households) in each quintile in the market.

Households with missing income data are allocated across income bands in proportion to the households in their market with non-missing income data.

We inflate 2023 population numbers to account for population growth between 2023 and 2025, assuming the national rate of population growth applies uniformly across the country and household income groups.

Figure 2 shows the distribution of market size, defined as the number of households in the market. Markets included are those where we permit entry, and they are distinguished by how urban they are. The figure shows more urban markets tend to be larger. No markets in rural areas meet our criteria for entry.

Figure 2: Distribution of households in markets that permit entry by how urban they are



3.4 Static base case without entry

This section describes the set-up of the static model we use to analyse competition within each market at a point in time before the entrant enters. Additional details of the model and mathematical derivations are provided in Appendix A.

3.4.1 The household's problem

Households in our model are approximate utility maximisers. Each household chooses just one supermarket store to shop at by considering average prices and other store characteristics. At their chosen store, they decide what quantity to buy based on price. We next discuss each of these aspects in more detail.

We assume households undertake a single 'main shop' at their chosen supermarket store. This assumption reflects a finding by the Commerce Commission, 2022 (at paragraph 4.30) in its grocery sector market inquiry that 84% of consumers do a main shop. A main shop is defined by the Commerce Commission as a shop happening at a regular interval based on the convenience of using one supermarket to get all the household's groceries in one place.

This can be conceptualised as households choosing between heterogeneous goods, where each 'good' is a store characterised by a price for the basket of groceries they expect to buy and other qualities of the store as a whole. The simplification is for analytical tractability. It ignores that consumers buy many different types of item at the supermarket, potential differences in the quality of products offered at each store, and within-store differences in prices for different items. We assume every store offers a sufficient range of products that households can conduct a full weekly shop for all types of grocery item there, but within product types some stores offer a wider range of choices than others.

We model competition between two incumbent supermarket firms in a market m. The remainder of our analysis applies to each market, and therefore to simplify the notation we omit the subscript m. Each incumbent potentially owns multiple stores in a given market. We index stores within a market by $j = 1, 2, ..., J$, for a total of J stores in the market. A household i in income group g that chooses store j gets utility:

$$U_{ijg} = -\alpha_g b_g p_j + \beta_g \ln A_j + \gamma_g X_j + \xi_{ijg} \tag{2}$$

where p_j is price per item, A_j is the breadth of assortment of items (number of SKUs), and X_j is the customer experience offered (convenience, amenities, service quality, etc). The parameter b_g is basket size, an exogenous measure of the number of items purchased in the shopping basket for a household in income quintile g, such that $b_g p_j$ measures the price for the basket.

Equation (2) is a utility function that is widely employed in the economics literature for analysing competition with differentiated products (e.g., Berry et al., 1995; Nevo, 2000). In our specification, price and experience enter the utility function linearly, while assortment enters in log form to reflect diminishing marginal utility from additional product variety.

The parameters in equation (2) that we calibrate (see Section 4) from the literature are the sensitivity of utility to basket price, α_g, log assortment, β_g, and experience, γ_g. The error term ξ_{ijg} captures unobserved factors that influence store choice, such as proximity to work, or habit. It is assumed to be independent and identically distributed (i.i.d) across household-store pairs and Type I extreme value distributed, meaning household store choice can be modelled as a multinomial logit.

We denote the deterministic component of utility (equation (2)) by V_{jg}. Here we omit the i subscript because the deterministic part of utility varies only at the income quintile-store level. That is,

$$V_{jg} = -\alpha_g b_g p_j + \beta_g \ln A_j + \gamma_g X_j \tag{3}$$

We define $j = 0$ as the outside option, which gives utility for household i in income quintile g of $U_{i0g} = V_{0g} + \xi_{i0g}$.

Application of the logit model gives the following share of households within income quintile g choosing store j:

$$s_{jg} = \frac{\exp(V_{jg})}{\sum_{j=0}^{J} \exp(V_{jg})} \tag{4}$$

The share of households within income quintile g choosing the outside option is given by:

$$s_{0g} = \frac{\exp(V_{0g})}{\sum_{j=0}^{J} \exp(V_{jg})} \tag{5}$$

In the literature, the share of the outside option is sometimes normalised to zero (see, for example, Berry et al., 1995). However, we have data that allow us to calibrate this share, which we do in Section 4.

The quantity (number of items) demanded by a household in income quintile g at store j is given by:

$$q_{jg} = \theta_{0g} + \theta_{1g} \ln(p_j) \tag{6}$$

In equation (6), θ_{0g} and θ_{1g} are the parameters to be calibrated, both of which are allowed to vary by income quintile to reflect the facts lower income households tend to purchase lower quantities and be more price-sensitive. We expect $\theta_{1g} < 0$, to reflect that as prices increase, quantity demanded falls. We use the semi-log functional form to capture diminishing sensitivity: as prices get to higher levels, the rate of decrease in quantity demanded slows down.

Note households as we model them are not perfect utility maximisers. They select the store to shop at considering only how the price they pay for their basket will affect their utility, but when they come to make purchase decisions they vary how much they buy depending on price, which has additional effects on their utility. We make this simplifying assumption for tractability reasons, but it reflects the plausible situation in which shoppers do not compare the prices of all their intended purchases before choosing where to shop, but rely on overall impressions of price level and rules of thumb.

3.4.2 The incumbent's problem

The two incumbent duopolists d own existing stores as described above. In the static base case, we take the existence of these stores as given. That is, no entry of new stores and no exit of existing stores occurs.

We treat the assortment and customer experience offered by each store as exogenous and derive values from data. This procedure is described in Section 4. We ignore the presumably fixed costs associated with delivering a given level of customer experience because these will not affect optimal pricing decisions given customer experience is exogenously set.

Based on the demand curves of each income quintile derived above, the market demand curve faced by store j is given by:

$$Q_j = \sum_g M_g s_{jg} q_{jg} \tag{7}$$

Each incumbent duopolist d with supermarkets $k \in \mathcal{K}_d$ in a given market thus has profit across all these supermarkets of:

$$\Pi_k = \sum_{k \in \mathcal{K}_d} (p_k - c_k) Q_k \tag{8}$$

where c_k is the marginal cost of an item. This cost is derived from data as described in Section 4 and allowed to vary across stores. The incumbent chooses prices to maximise profits over all stores that it owns in a given market. The first-order conditions for this multi-store joint pricing profit maximisation are derived in Appendix B. We solve the first-order conditions to determine optimal prices and quantities in the static base case.

Our model assumes that the incumbents compete by setting prices (rather than quantities) to maximise profits and that consumers do not consider different stores in the same market to be perfect substitutes for each other. This is a standard model of Bertrand competition with differentiated goods (Budzinski and Ruhmer, 2010). In the case of supermarkets, the Commerce Commission has described the incumbents as providing consumers with differentiated offerings, including across price, quality of service, convenience, and shopping experience (Commerce Commission, 2022, at paragraphs 2.35 and 2.36). It also found that, while there are other factors that the incumbents compete on to drive consumer store choice, price-related factors appear to be the key driver (Commerce Commission, 2022, at paragraph 4.72).

Bertrand competition assumes firms will react to the price-setting behaviour of their rivals, because decreases in rivals' prices result in consumers switching to another firm (Budzinski and Ruhmer, 2010). This drives incumbents to set lower prices in markets that are subject to entry by an entrant that offers lower prices.

Our model of competition makes simplifying assumptions regarding the incumbents' pricing for analytical tractability. For example, it assumes incumbent pricing responses to the entrant apply on average across the basket of goods we model, rather than through lowering the price of specific goods that compete with the entrant's products (while keeping other prices fixed or even increasing them). It also assumes the items sold do not vary in quality, and the incumbents do not respond to the entrant by altering the quality mix of the products they purchase. Lastly, in practice Woolworths operates a national pricing model and Foodstuffs operates a co-operative pricing model in each of the North and South Islands (see Commerce Commission, 2022, paragraph 4.138). However, we assume under the threat of entry both incumbents could adopt a more flexible pricing system as provided for by our model of competition.

3.5 Static case with entry

After modelling a static base case with no entry, we model a static 'entry case', where an entrant has entered each market. We do this with and without a regulatory intervention that reduces labelling costs. To simplify the analysis, we assume that there is (at most) a single entrant in each market. This is not unrealistic, given entry in recent years has been very limited. Further, the Commerce Commission finds that New Zealand's size and population profile make large-scale entry difficult, although it also finds the market could sustainably accommodate at least one more large-scale rival (Commerce Commission, 2022, p.189 and paragraph 6.42).

We model our entrant as a hard discounter, which is a format that focuses on offering low prices, a narrow product range (limited SKUs) and other low-cost strategies such as a minimalist store experience. We use this format for three reasons. First, it is consistent with the view recently expressed by the Commerce Commission that, with price being a key consideration for shoppers, price competition from hard discounters with a narrow product range may be a way for an entrant to meet current and future customer preferences (Commerce Commission, 2024a, p.26). Second, it aligns with the Bertrand competition model where the incumbents compete on price, allowing us to consider an entry format that focuses on the dimension of competition that matters most within this model. Third, a hard discounter may face lower barriers to entry, particularly relating to the need to find appropriate real estate; the option of opening a store with a smaller floor area and non-standard layout means many existing buildings could be converted into stores.

We assume prices for the entrant are set exogenously, at some fraction δ below the unweighted median price offered by incumbent stores in the market in the base case. That is, the entrant's price p^e_{ent}, is given by:

$$p^e_{ent} = (1 - \delta)\tilde{p}_m \tag{9}$$

where $\tilde{p}_m$ is the unweighted median price across all incumbent stores in market m.

Additionally, we assume the entrant's marginal costs are some percentage below household-weighted national average incumbent marginal costs in the base case (which are calibrated in Section 4), where the percentage discount depends on how urban the market is. As noted earlier, markets are classified to levels of urbanness according to the most urban of their constituent SA2s. We assume markets in major urban areas have the lowest marginal costs for entrants, markets in large urban areas have higher costs, and markets in other areas have the highest costs. These distinctions capture the ease of distribution to stores in different types of market. They are also consistent with the Commerce Commission's finding that scale is a key factor in providing cost advantages, which is affected by population density (Commerce Commission, 2022, paragraphs 6.118 and 6.26).

In the static entry case with the product labelling regulatory intervention, the entrant's marginal costs are assumed to be an additional 20 cents per item lower than in the static entry case without the regulatory intervention.

We assume entry of the entrant does not affect the costs of the incumbents. If the entrant were to use the same supply chains and compete with incumbents for inputs, for example, this assumption might not hold. However, an entrant that planned to leverage separate supply chains from exporting countries whose labelling regulations are not consistent with New Zealand's, which is the type of supermarket chain most likely to be affected by changes in labelling regulation, can plausibly be assumed to have little or no effect on incumbent costs.

To fully capture a dynamic seen with supermarket entry overseas, that hard discounter entrants to a market often struggle to gain market share,[3] we assume only a certain proportion of households in each market will consider shopping at the entrant store. This captures the fact not all households would consider doing their main shop at a hard discounter store and that not all households might know about the entrant store. The proportion of households that consider the entrant store is assumed to decrease with household income. This assumption also helps to ensure realistic increases to consumer surplus from an entrant despite the multinomial logit's well-known tendency to overstate utility gains from choice (discussed in more detail in Appendix A).

Formally, we define a fraction λ_g of households in income quintile g that will consider switching to the entrant. We calculate the share of households choosing store j in the actual entry case as $1 - \lambda_g$ times the share of households choosing store j in the base case (where entry has not occurred) plus λ_g times the share of households choosing store j in the unweighted entry case.

In the cases with and without the product labelling regulatory intervention, we re-solve the first-order conditions in each market assuming entry and using these weighted average shares to determine incumbent optimal prices and quantities for all stores.

4 Static model calibration

4.1 Base case data

4.1.1 Prices

Optimal prices are endogenously determined in our model from the first-order conditions for profit maximisation. However, we use data on observed prices to calibrate some of the model parameters (see Section 4.4) and to make some adjustments to the profit and consumer surplus calculations to produce more realistic values (see Section 5).

We determine observed prices at supermarkets across New Zealand by pricing a basket of five essentials: milk; bread; butter; cheese; and toilet paper. We use specific well-recognised brands for each item, so as to maximise the number of stores that sell the exact five items. We calculate the total price of this basket using price data from the price comparison website Grosave,[4] for the supermarkets listed on that website. Where items were missing from the basket at the time of collecting these data, we imputed the price by using the modal price for that item across other supermarkets with the same banner.[5]

Having determined the price for our essential items, we sought to scale this price up to reflect the price of a broader basket of items that might typically be bought by a consumer in their weekly main shop. To do so we used Consumer NZ data on the national average price for a basket of 22 items, which were available for Pak'nSave, New World, and Woolworths (Castles, n.d.). Using our five-item basket, we calculate the ratio of the price at each supermarket to the average price across all supermarkets within a given banner. We then apply this ratio to the national average price for the basket of 22 items in each banner, giving us a price for this basket at each supermarket in New Zealand.

[3] Commerce Commission, 2024b finds that hard discounter entrants in Australia and Finland have had an impact, but it is a 'slow process' to capture market share.

[4] https://grosave.co.nz/home, accessed on 6 November 2025

[5] For FreshChoice, every store had at least the specific milk item we priced missing. We therefore used the modal price of milk at New World to impute a milk price for FreshChoice.

We do not have sufficient data to make this calculation for some supermarkets. While we have FreshChoice prices for the five-item basket, we do not have a national price for the 22-item basket to make the above adjustment. We therefore impute a 22-item national average price for FreshChoice by adjusting the New World 22-item national average price by the ratio of FreshChoice average price to New World average price for the five items.

For SuperValue and Four Square, pricing data were not available from the sources referred to above. For SuperValue, we collected pricing data for our five-item basket from its website. For Four Square, we collected prices for our five-item basket in-store from a sample of stores, by in-person visits and phone calls. As with FreshChoice, we adjusted these five-item basket prices to the 22-item basket by reference to the ratio of the average price for the five-item basket for each store to the equivalent average price for New World.

The above approach gives us observed prices for a 22-item basket at all supermarkets across New Zealand owned by the incumbents that are listed on the Grosave website. We divide the total price by 22 to get a price per unit, which we use in our parameter estimation as discussed later. We observe prices for 426 stores.

A number of supermarkets that are not listed on the Grosave website are included in our model (discussed in Section 3.2). For these supermarkets, we used the following rules to impute observed prices. These rules are applied in order, with prices imputed in earlier steps used to impute prices in later steps. They are also distinguished by 'metro' and 'non-metro' stores, where a metro store is one that is specifically identified as such in the name of the store.

- For non-metro stores in markets where other stores of the same banner have non-missing prices: We impute missing prices using the unweighted average of the non-missing prices for the banner in the market. This rule does not apply to metro stores and metro stores are not used to calculate the average price for the banner. We impute prices for 19 stores by this method.

- For non-metro stores in markets where no other stores of the same banner have non-missing prices:

  - We start by calculating, for every banner and every market where that banner is present (with non-missing price and not a metro store), the unweighted average price of the banner.
  - For each banner other than the banner for which we are seeking to impute prices:
    * We focus on markets in which at least one store of the banner to be imputed and at least one of the other banner have non-missing prices.
    * In each such market we calculate the ratio of average prices for the banner for imputation to average prices for the other banner.
    * We take the unweighted average of these ratios across the markets we have focussed on (call this the 'all market average ratio', which applies for each banner).
  - For each store in the banner for imputation, we calculate what the price at the imputed store would be if its ratio of average prices to the average prices of each other banners in that same market were the same as the all market average ratio for a given banner.
  - This gives us a set of imputed prices for the relevant store by comparing against each banner. We impute the price in the store of interest as the average of the prices implied by comparisons with other banners. We impute prices for 194 stores by this method.

- Metro stores: We apply the process described in the step above to get a predicted price for all metro stores with non-missing prices, and calculate the average ratio of predicted price to observed price. We apply this ratio to the predicted prices for metros with missing prices to impute their prices. We impute prices for 4 stores by this method.

- All stores that still have missing prices have these imputed as the banner medians. We impute prices for 54 stores by this method.

4.1.2 Assortment

The variable A_j reflects the assortment in each of the incumbents' supermarkets, as measured by the number of SKUs. To determine SKUs at each store, we use data provided to the Commerce Commission by Foodstuffs and Woolworths for the Commission's 2024 Annual Grocery Report (Commerce Commission, 2024a). These data cover only the New World, Pak'nSave, and Woolworths banners, and some stores with these banners are missing; they cover 390 stores in total. To address this, we supplement these data with 2021 SKU data from the Commission's 2022 grocery market study (Commerce Commission, 2022), which also cover the Four Square, FreshChoice, and SuperValue banners. Because in most cases where a store has non-missing SKUs in both data sets the two values differ, we run a linear regression of 2024 SKUs on 2021 SKUs and banner fixed effects across the stores included in both data sets. We use the regression equation to predict 2024 SKU values for the 273 stores with 2021 data but no 2024 data.

In addition, some stores have opened since 2024 and are included in neither data set. For these stores, we used an internet search to identify details on the store opening, which in five cases provided information on SKU numbers and in 11 cases provided information on retail floor area.

Where we still cannot determine SKU numbers for a store, but are able to identify gross floor area or retail floor area from our web search or the Commission data set, we use the relationship between floor area and SKUs in the Commission data to predict SKUs. First we regress SKUs on retail floor area separately for stores with retail areas of no more than 2000 square metres and retail areas above 2000 square metres. We include banner fixed effects to allow for different banners to use different approaches to arranging their stores. We allow the relationship to differ for stores above and below 2000 square metres because visual inspection shows the slope of the relationship changes at this store size. This imputation approach gives predicted SKUs for 13 additional stores. We then regress SKUs on gross floor area for stores above and below 3500 square metres, again including banner fixed effects, and use the estimated relationships to impute SKUs for the one additional store that has gross floor area data but not retail floor area data. For the remaining 15 stores, we impute using average SKUs for the banner.

4.1.3 Customer experience

Experience, X_j, is a measure capturing the quality of the customer's supermarket experience, covering aspects such as store layout, car parking, number of checkouts, and having a loyalty programme. To measure experience, we start from a customer survey set out in Commerce Commission, 2022 that asked respondents what attributes they value in selecting where they undertake their main supermarket shop. Figure 3 shows the survey results. Many of the responses in Figure 3 relate to prices (e.g., 'low prices overall'), assortment (e.g., 'wide choice of products'), or geographic proximity (e.g., 'convenient/easy to get to'), which are already captured in other terms in equation (2) or in our geographic approach to defining markets. Other responses are difficult to find store-level data for. Excluding these responses, we are left with the following seven attributes, which we use to measure experience:

- Familiarity with the store/service: we measure this at the banner level using the results of a survey by Canstar Blue that ranked the supermarkets on a set of attributes, with results presented on a scale of 1 to 5 (Canstar Blue, 2024). We focus on the survey results for 'layout and presentation of the store' and 'customer service and accessibility of staff', and weight together the survey results using equal weightings. The Canstar Blue survey did not have data for SuperValue, so we assume it has the same values as Woolworths.

- Good quality products: we again use the Canstar Blue survey results to measure this at the banner level, using the survey results for 'freshness of produce' (acknowledging that the focus on produce does not capture the quality of *all* products, but is a reasonable proxy).

- Have a loyalty card: we draw on public information at the banner level to determine a binary value of whether a supermarket has a loyalty card scheme or not.

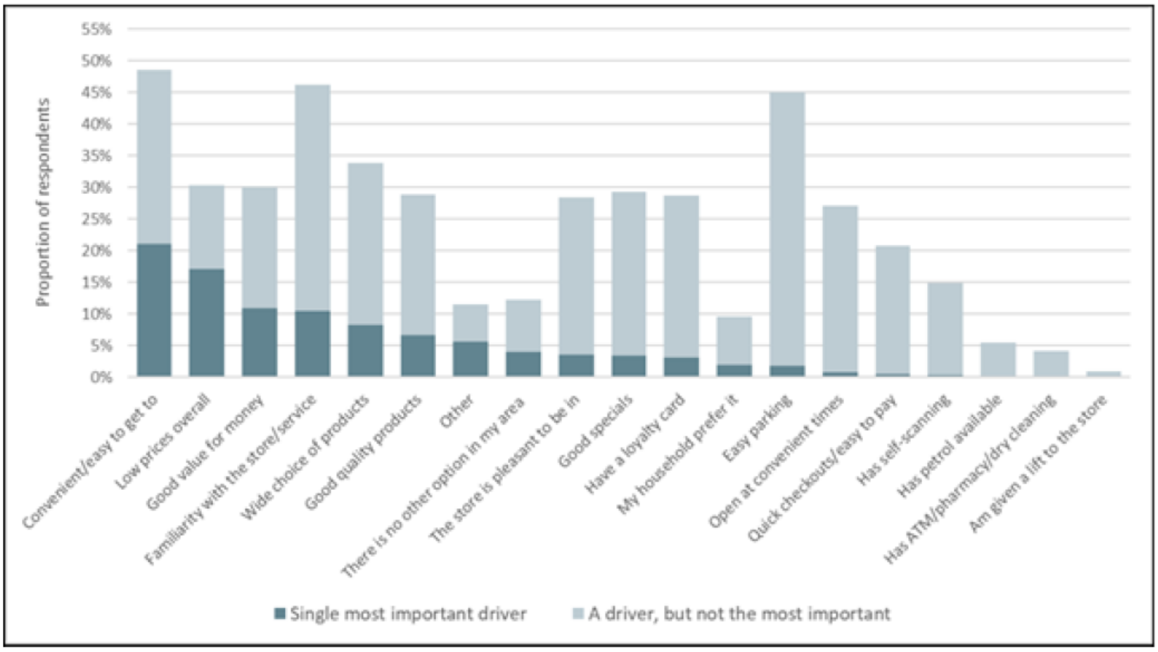
- Easy parking: we measure the ease of parking using data provided to the Commerce Commission for the 2024 Annual Grocery Report (Commerce Commission, 2024a) showing, for every supermarket across New Zealand, the number of car parks. The absolute number of car parks may simply reflect the size of the store, so we control for size by calculating car parks per square metre of store floor area (also from the Commerce Commission data).

- Open at convenient times: we measure the convenience of opening times by calculating the total hours per week that the store is open, based on the Commerce Commission's data on opening hours at the store level.

- Quick checkouts/easy to pay: we measure this by analysing the total number of checkout lanes per square metre of store floor area. Data on the number of lanes are also included from the Commerce Commission's data for each supermarket across New Zealand.

- Has self scanning: we measure this using a binary value as to whether a supermarket has self-serve checkouts or not, which is again included in the Commerce Commission's data at the store level.

Figure 3: Drivers of store choice in New Zealand (Source: Figure 4.3 of Commerce Commission, 2022)



We use the percentages in Figure 3 for each of these seven attributes, rescale to sum to 100%, and use these as weights to calculate a weighted score across the seven attributes for each supermarket. While this gives experience scores by store, there are a number of stores which have missing data, due to gaps in the Commission's dataset. For this reason, and for model simplicity, we do not estimate an experience score at the store level, but calculate an average experience score at the banner level. We normalise these scores using min-max normalisation (Han et al., 2012, p.114) to rescale in the range of $[0.2, 1]$, setting the highest score (for New World) to 1 and the lowest score (for Four Square) to 0.2 (we do not set this to zero to allow the entrant to come in with a lower experience score). The resulting experience scores are: New World, 1; Woolworths, 0.96; FreshChoice, 0.82; Pak'nSave, 0.80; SuperValue, 0.48; and Four Square, 0.20.

4.1.4 Outside option

We estimate the share of consumers who shop at the outside option, s_{0g}, using data in the Commerce Commission's 2024 Annual Grocery Report (Commerce Commission, 2024a), as shown in Figure 4. These data give the share shopping at supermarkets other than those of the incumbents by region, ranging from 29% for Auckland to 7% for the West Coast/top of the South Island. We match SA2s to each region, thereby giving us a value for the outside option for each SA2. In most cases, all SA2s within a given market have the same value for the outside option. Where SA2s within a given market have different values for the outside option, we take the average across the SA2s constituting the market.

Figure 4: Market share of Regulated Grocery Retailers (RGRs) and Others by region in 2024 (Source: Figure 9 of Commerce Commission, 2024a)

4.1.5 Costs

For each incumbent's variable costs, we utilise financial data provided to the Commerce Commission by Foodstuffs and Woolworths for the 2024 Annual Grocery Report (Commerce Commission, 2024a). We assume variable costs are given by the total cost of goods sold recorded in the financial data, with all other costs reflecting fixed costs. We determine cost of goods sold for each banner at the North and South Island level for Pak'nSave, New World, Four Square;

and at the national level for Woolworths and FreshChoice (because data by island are not available). We then calculate these costs as a percentage of revenue (drawn from the same financial data). For every store in our data for a given banner, we estimate that store's variable costs by applying this percentage to the observed prices.

4.1.6 Household expenditure by income quintile

We determine a baseline value for expenditure on groceries in each income quintile by identifying categories in Statistics New Zealand's HES data that are likely to be purchased at supermarkets (at the 2-digit level).[6] We then gather data on household expenditure for 2023 for these 2-digit categories by income grouping. There are 10 income groupings in the data, and we aggregate adjacent groupings to give household expenditure for income quintiles. We inflate this to a 2025 value using the change in the Consumers Price Index. This baseline value for expenditure is used to determine the basket size parameter, b_g, for each income quintile.

4.2 Entry case data

4.2.1 Entrant prices and costs

We assume that the entrant's prices are exogenous, and in each market we set these at 25% below the unweighted median price for the incumbents, as determined by our model optimisation. We draw evidence for this price discount from that offered by hard discounters elsewhere in the world. We look in particular at Aldi, a German-owned supermarket chain operating a hard discounter model across around 20 countries, and Lidl, another German-owned hard discounter operating across around 30 countries. In Australia, Aldi has noted that it maintains a price gap of 15-20% from its competitors (Australian Competition and Consumer Commission, 2025). Also, US consumer organisation Consumers' Checkbook finds Aldi's US prices are 30-40% lower than an average across all other stores, and Lidl's are about 20-25% lower (Brasler, 2025). We therefore use a preferred estimate of 25%, and sensitivity test a range of 15% to 35%.

We also assume that the entrant's variable costs are lower than those of the incumbents. The entrant's limited range and store experience are likely to provide it with cost advantages. We were not able to source data on the lower costs of hard discounters to estimate this advantage. However, we sourced data on the lower margins of hard discounters. In particular, we use 2023-24 data in Australian Competition and Consumer Commission, 2025 (Figure 1.3) on the margin of Aldi relative to Coles and Woolworths in Australia, showing that Aldi's margin is 83% and 88% lower than the margins of Coles and Woolworths respectively. Calculations based on UK data from Competition and Markets Authority, 2024 (see Figures 2.1 and 2.3, using 2022-23 data) give a wider range, with Aldi's and Lidl's margins ranging from 55% to 98% below the margins of the incumbents (Tesco, Sainsburys, Asda, and Morrisons). This range from the CMA data encompasses the range from the ACCC data.

To apply these percentage margins in our own case, we assume an incumbent price of \$6 and costs of \$4.80 (giving a margin of \$1.20). We take the entrant's price as 25% below the median price of the incumbents (as above), calculate the entrant's margin as being 55% to 98% below the incumbents margin, giving the entrant's margin range of \$0.024 to \$0.54. From here we back out the entrant's costs, giving a range of \$3.96 to \$4.476. This shows that the entrant's costs range from 7% to 18% lower than the incumbents costs (of \$4.80).

Based on this analysis, and rounding to reflect uncertainty, in our central scenario we assume the entrant's costs are 10% to 20% lower than the household-weighted national average marginal costs of the incumbents. We vary this depending on the urban/rural nature of the area, with costs likely to be lower in more urban areas due to greater cost efficiencies that can be achieved

[6] These categories are: fruit and vegetables; meat, fish, and poultry; grocery food; non-alchoholic beverages; alchoholic beverages; cigarettes and tobacco; other household supplies and services; and personal care.

from increased population density. We thus assume the entrant's costs to be 20% lower than the incumbents' in main urban areas, 15% lower in major urban areas, and 10% lower everywhere else.

While incumbent annual fixed costs play no role in incumbent behaviour in our model, we use them to estimate annual fixed costs for the entrant, which affect entry decisions. Annual fixed costs are drawn from the Commerce Commission financial data referred to earlier, which are available at the banner and island/national level. To determine the entrant's annual fixed costs, we start with annual costs for the incumbents from the Commerce Commission data (at the banner and island/national level), where we use all costs (other than cost of goods sold) prior to calculation of EBITDA. The entrant's annual fixed costs at the store level are likely to vary by store size (larger stores are likely to incur higher costs from more staff, higher electricity costs, etc) and the market the store is located in (more urban areas are likely to incur higher rental costs). To capture these factors, we calculate the annual cost per SKU for the incumbents. These costs are highly variable, ranging from approximately \$15/SKU to \$1,000/SKU; we exclude costs per SKU for two banners at these end points as being relative outliers, as well as costs per SKU for New World, because the entrant's discounter model is materially different. This gives a range of \$50/SKU-\$300/SKU, with a midpoint of \$175/SKU. We apply a further 10% discount to reflect the lower costs of the entrant, and apply this to the entrant's assumed number of SKUs (2,800 as our preferred value, discussed below). This gives an entrant's annual fixed cost of \$433,125 per store at the midpoint.

This calculation captures how costs reflect the entrant's store size (proxied by SKUs) but not how they reflect where the store is located. For this, we make an adjustment based on the urban/rural area the store is located in. We normalise a weight for medium urban areas to 1, and assume higher weights for major urban (1.5) and large urban (1.25), and lower weights for small urban (0.75) and rural (0.5). We apply these weights to the \$433,125 annual cost depending on the urban/rural area the entrant's store is located in, to give an estimate of the annual cost. Since the financial data are 2024 cost values, we inflate to 2025 values by increasing all values by 3.4%, reflecting the change in Statistics New Zealand's Producer Price Index (inputs) for the supermarkets, groceries and specialised food retailing industry, for the year to June 2025.

We assume the entrant also incurs one-off entry costs each time it enters a new market. These include costs such as acquiring land, obtaining consents, and building and outfitting the supermarket. While it may be that the entrant can lease an existing building suitable for a supermarket, rather than build a new one, our approach implicitly assumes any ongoing lease costs are capitalised into the one-off land and building costs. To estimate these costs we draw on information on the costs of building a new supermarket, based on recent public announcements by the incumbents. We found information on nine supermarkets that have been opened since 2018, and matching this up with SKU data find that the cost per SKU ranges from approximately \$3,000/SKU to \$15,000/SKU. However, because our entrant is a hard discounter, it will offer a limited SKU range, and therefore we look only at stores that offer a lower SKU range (although even this ranges from 4,000 to 13,000 SKUs, as the hard discounter model is not currently present in New Zealand). From this we obtained costs of \$200/SKU to \$1,500/SKU. Applied to the entrant's SKU range of 2,800 SKUs this gives an entry cost of \$0.55m to \$4.125m, with a midpoint of \$2.3375m.

We also considered applying a 10% discount to this, to reflect the lower costs of the entrant. However, one factor that we have not accounted for in the above analysis is the cost of establishing distribution centres. This is likely to be a relatively lumpy cost, and it is difficult to determine both the precise cost and the rate at which the entrant might expand its distribution network. To reflect this, we have not applied the 10% discount to the entry cost. That is, while there may be a discount reflecting the entrant's lower costs, there will also be higher costs associated with distribution centres, and we assume that these offset.

4.3 Entrant assortment and experience

The hard discounter business model is focused on a limited range of SKUs. In Australia, Aldi generally stocks between 1,800 and 2,000 SKUs (Australian Competition and Consumer Commission, 2025). Similarly, in the US, Aldi stores generally stock between 1,600 and 2,000 SKUs (International Supermarket News, 2025). In Germany, Aldi stores offer around 2,000 SKUs, while the other hard discounter Lidl offers around 4,500 SKUs (Beer, 2024). Other sources consider hard discounters more generally and provide a range of 2,000 to 4,000 SKUs (Bishop, 2017).

Based on this, we use a SKU range for our entrant hard discounter of 1,600 to 4,000, with a preferred value at the midpoint of 2,800.

For the entrant's customer experience value, the hard discounter model is based on a very limited store experience, including fewer staff, no loyalty programme, minimal decor, no in-store bakeries or deli counters, and fewer checkouts, with customers bagging their own groceries. We therefore assume that the entrant has a very low experience value, considerably below those of the incumbents, where the minimum was for Four Square at 0.2. We use a range of 0 to 0.1, and choose a preferred value of 0.05.

4.4 Parameter values

We start by deriving values for the parameters of the utility function (equation (2)) and the basket size function (equation (6)), all of which are allowed to vary by income quintile. We do not have directly observable values for these parameters, but calibrate them based on elasticities and other values from the literature. Specifically, we match values from the literature for the store choice elasticity with respect to price, the store choice elasticity with respect to assortment, the sensitivity of utility with respect to experience, and the elasticity of basket size with respect to price. The expressions for these values depend on price and market share, both of which are ultimately determined endogenously by our model and vary at the store level. We thus need to choose the price and market share at which to match the values from the literature. We use observed prices since we have these as an exogenous price measure, but since we have no similar exogenous measure of shares, we use shares predicted by the model. Because this gives us store-level elasticities, we calculate household-weighted averages across stores across the whole country and match these to the values from the literature for each income quintile.

Because the market shares predicted by our model depend on the parameters in the utility function, we use an iterative procedure to find all the parameter values that simultaneously yield the elasticities from the literature. Specifically, we update each parameter in turn based on the market shares predicted by the current values for the other parameters, recalculate market shares based on the new parameter values, and repeat this procedure to convergence. We consider we have achieved convergence when the largest change in any parameter from the previous iteration is no greater than 0.00005.

The following subsections describe in more detail the values we take from the literature and how we use them to calculate the parameters of the utility and basket size functions within an iteration. They also describe calibration of the proportion of households that would consider shopping at an entrant store.

4.4.1 Deriving α_g, the sensitivity of utility to price

To determine a value for α_g, the price sensitivity of utility, we derive an expression for the 'store-choice own-price elasticity' (the percentage change in probability of choosing store j for a 1% change in its price) from equation (4), the market share equation derived from our utility function. We denote this elasticity by $\epsilon_{jj,g}$ (see also Train, 2009, p.59):

$$\epsilon_{jj,g} = -\alpha_g b_g p_j (1 - s_{jg}) \tag{10}$$

If we take a value of $\epsilon_{jj,g}$ from the literature, basket size b_g derived from data as described above, observed price p_j and a value for s_{jg} implied by our model, a simple rearrangement of this equation allows us to back out α_g.

Bell et al., 2000 estimate a logit model for store choice and derive a formula for the store choice elasticity similar to equation (10) but excluding the term in p_j (since p_j enters their utility function in logged form). They calculate values for the equivalent of α_g of -2.201 for shoppers at stores with 'every day low prices' and -3.233 for shoppers at stores with promotional prices (see Table 4 in Bell et al., 2000). They also report descriptive statistics (in their Table 3) for the market share, ranging from approximately 10% to 60%, which gives a midpoint of 35%. Using this midpoint, and the equation in Bell et al., 2000 for the store choice elasticity, we calculate values equivalent to $\epsilon_{jj,g}$ in equation (10) of -1.4 and -2.1. Assuming more inelastic store choice for higher income quintiles and that the elasticity decreases linearly across the income quintiles, we have $\epsilon_{jj,g}$ for income quintiles $g = 1, ..., 5$ of -2.1, -1.925, -1.75, -1.575, and -1.4 respectively.

4.4.2 Deriving β_g, the sensitivity of utility to assortment

To determine a value for β_g, the assortment sensitivity, we use the market share equation (equation (4)) to derive the store-choice elasticity with respect to assortment, which we denote by $\zeta_{jj,g}$:

$$\zeta_{jj,g} = \beta_g (1 - s_{jg}) \tag{11}$$

We draw on the literature to find a value for $\zeta_{jj,g}$. Sethuraman et al., 2022 estimate the percentage change in the net benefit of assortment for a change in assortment size, which we use as a proxy for the store-choice elasticity with respect to assortment. They find a mean assortment size benefit elasticity of 0.08 and a grocery-specific elasticity of 0.13. We use the grocery-specific elasticity, because it is more relevant to our analysis. We are not aware of any studies that show how this elasticity varies by income group, although Sethuraman et al., 2022 cite studies supporting the proposition that assortment size is more beneficial for higher-income consumers that seek variety, suggesting a larger elasticity. We assume that the middle income quintile has an assortment size elasticity equal to the study result of 0.13, and use an increment of 0.01 in either direction across income quintiles, giving $\zeta_{jj,g}$ for income quintiles $g = 1, ..., 5$ of 0.11, 0.12, 0.13, 0.14, and 0.15 respectively.

4.4.3 Deriving γ_g, the sensitivity of utility to customer experience

The parameter γ_g is the sensitivity of utility with respect to experience. As a proxy for this value, we draw from Smith, 2002, who estimates a model of consumer choice for the UK supermarket industry. Smith, 2002 estimates a utility function that increases linearly with whether or not a supermarket offers car parking, along with variables for price, supermarket size, and distance to other supermarkets. While our experience score covers more than just car parking, car parking has the second highest weighting of the experience attributes we analyse, and we use car parking in this instance as a reasonable proxy for the broader set of attributes. Smith, 2002 (Table 6) estimates the coefficient on the car parking dummy variable for different income groupings, ranging from 0.25 for low income to 0.60 for high income. We use these values for the low and high income quintiles in our model, and assume that γ_g increases linearly across the income quintiles, giving values of γ_g for income quintiles $g = 1, ..., 5$ of 0.25, 0.34, 0.43, 0.52, and 0.60 respectively. These values do not change as we iterate the other parameters.

4.4.4 Deriving θ_{1g}, the sensitivity of basket size to log price

To derive θ_{1g}, we define the price elasticity of basket size for group g as:

$$\eta_g = \frac{\partial q_{jg}}{\partial p_j} \frac{p_j}{q_{jg}} \tag{12}$$

Using equation (4) we can write this as:

$$\eta_g = \frac{\theta_{1g}}{q_{jg}} \tag{13}$$

We can therefore draw values for the price elasticity η_g from the literature, and use these, our measure of basket size b_g derived from data, observed price p_j, and equation (13) to derive an implied value of θ_{1g}. Because price varies at the store level, this calculation yields a value of θ_{1g} that similarly varies at the store level for each income quintile. We thus calculate θ_{1g} for each income quintile by taking the household-weighted average across all stores in the country.

Andreyeva et al., 2010 review 160 US-based studies on the price elasticity of demand for major food categories, and find mean values ranging from -0.3 to -0.8. Nghiem et al., 2011 review New Zealand elasticities for 22 food categories, and find elasticities ranging from -0.1 to -1.0, depending on the category (albeit only one category, potatoes and kumara, has the -0.1 elasticity, and the closest elasticity to this is -0.3). Mhurchu et al., 2013 calculate New Zealand elasticities by income quintile and food group. Excluding two outlier groups (pork and energy drinks, with very elastic demand) and non-supermarket food groups (restaurant food and ready-to-eat food), the average elasticity is -1.4 for the lowest income quintile and -1.0 for the highest income quintile.

Mhurchu et al., 2013 recognise that their elasticity estimates are high (in magnitude) relative to international estimates. They suggest several reasons for this, some of which relate to data quality (e.g., the short measurement period of their analysis) and others have a conceptual basis (e.g., New Zealand is a major food producing country, meaning substitutes are readily available). In any event, because of the relatively large results of Mhurchu et al., 2013, we use the lower values from Andreyeva et al., 2010 and Nghiem et al., 2011, and undertake sensitivity testing. In particular, we use an elasticity range for η_g of -0.3 to -1.0 for households in different income quintiles. Following the income relationship in Mhurchu et al., 2013, where those with higher incomes are less price sensitive, and assuming the elasticity decreases linearly across the income quintiles, gives η_g for income quintiles $g = 1, ..., 5$ of -1.0, -0.825, -0.65, -0.475, and -0.3 respectively.

4.4.5 Deriving θ_{0g}, the intercept in the basket size function

To determine θ_{0g}, we rearrange equation (6) as:

$$\theta_{0g} = q_{jg} - \theta_{1g} \ln(p_j) \tag{14}$$

This similarly yields a value of θ_{0g} that varies at the store level for each quintile; we again take the household-weighted average across all stores in the country.

4.4.6 Deriving λ_g, the proportion of the population that considers shopping at the entrant store

To determine a value for λ_g, the proportion of each quintile g that would consider the new store, we draw on Vroegrijk et al., 2013, who analyse how the entry of a hard discounter affects store patronage. In particular, they study consumer responses to the opening of Lidl stores in the Netherlands between 2002 and 2006, covering 140 outlets. They also disaggregate consumer responses across four segments, based on how prone consumers are to buying private labels and their focus on price and quality.

Based on the data in Vroegrijk et al., 2013, we calculate the shift in patronage to newly opened Lidl stores to range from 3% for consumers who are the least prone to private labels and more quality orientated, to 56% for customers who are the most private label prone and more price orientated.[7] Vroegrijk et al., 2013 measure patronage by counting all households that visit the store in the month, so this could include households that are trying out the hard discounter, not just those that have chosen it for their main shop. We thus interpret these patronage shifts as reasonable estimates of the percentage of households that consider the hard discounter stores.

The segments used in Vroegrijk et al., 2013 are unlikely to precisely match our income quintiles, though we expect higher income quintiles to be less prone to private labels and more quality orientated. To reflect this, we compress the percentages noted above, and use values of 50% for income quintile 1 and 10% for income quintile 5. We assume a linear change across the income quintiles, so use values of λ_g for income quintiles $g = 1, ..., 5$ of 0.5, 0.4, 0.3, 0.2, and 0.1 respectively.

5 Static model solution

In this section we explain how we solve the static model first-order conditions using a numerical approach to derive the optimal prices in the base case and entry case. Since these optimal prices are high relative to variable costs (which are based on observed data), we make an adjustment to these prices in our calculation of profits and consumer surplus, to ensure these are realistic. We also set out our approach to calculating profits, consumer surplus, and welfare, each of which is done in the base case, entry case without regulatory intervention, and entry case with regulatory intervention.

5.1 Solving for optimal prices

To solve the static model, we use the equation for the first-order conditions developed in Appendix B. The first-order condition applies for profit maximisation with respect to the price at store j, p_j, and therefore the solution involves a system of equations across the stores in the market. These equations are non-linear in prices, which creates complexities for determining analytical solutions to the first-order conditions. We therefore solve the first-order conditions numerically.

Our numerical solution is a best-response iteration involving the following steps:

1. Start with observed prices as the initial price guess for each store j.

2. Calculate the deterministic part of utility V_{jg}, share s_{jg}, and quantity purchased q_{jg} for households in each income quintile g, and aggregate to get total store demand across all income quintiles, Q_j.

3. Set up the system of equations for the first-order condition for all stores owned by each incumbent. We set this up as a Jacobian matrix, $\mathbf{D_d}$, where the diagonal elements are given by the own-price derivative for store j, $\frac{\partial Q_j}{\partial p_j}$, and the off-diagonal elements are given by the cross-price derivatives for store $k \neq j$, $\frac{\partial Q_k}{\partial p_j}$.

4. We solve the first-order conditions for $\mathbf{p_d}$, the vector of prices at each incumbent's stores, by solving $\mathbf{Q_d} + \mathbf{D_d}(\mathbf{p_d} - \mathbf{c_d}) = 0$, where $\mathbf{Q_d}$ is the vector of store demand and $\mathbf{c_d}$ is

[7] To calculate these figures, we use the shift in Lidl patronage from Table W4 in Vroegrijk et al., 2013 for each segment, and calculate as a percentage of each segment size. The segment size is calculated by taking the percentages in Table 6, and applying to total households of 9,425 from Table 8.

the vector of variable costs at the incumbent's stores. We do this sequentially for each incumbent (holding prices for the other incumbent constant).

5. We run diagnostic checks to flag cases where the results are nonsensical or the solution unstable, although we do not find any instances where these issues arise.

6. Using the updated prices from solving the first-order conditions, we repeat the above steps. We continue this loop until the greatest change in a price between iterations is no more than \$0.00001.

Completion of the above iteration gives us optimal prices for each of the incumbents' stores in the static base case. We similarly solve the modified first-order conditions for the static entry cases with and without the product labelling regulatory intervention to get optimal incumbents' prices in those cases. Note the entrant's prices are always exogenous, so they affect the optimal prices charged by the incumbents, but are not determined within the model.

5.2 Price adjustment

The optimal prices determined by solving the first-order conditions are high relative to the observed prices, and therefore also high relative to variable costs (since variable costs are calculated by reference to the observed prices). Price differences between the base and entry case derived from the model are likely to still be informative, but firm profits and changes in these calculated using model prices will likely be overstated. To correct for this, we instead calculate incumbent profits in the base case using observed prices.

There is no equivalent to observed prices for the entry case that can be used to calculate realistic profits; instead we calculate adjusted prices that capture the information contained in observed base case prices and the difference in prices between the base and entry cases predicted by the model.

For the incumbents, for store j, we have optimal prices in the base case, p_j^b, and in the entry case, p_j^e, and the observed price in the base case p_j^o. We need to determine an adjusted price in the entry case, p_j^a, that aligns more closely with the base case observed prices. One approach is to apply the absolute difference between p_j^b and p_j^e to p_j^o, but this risks generating large differences that push the adjusted price below costs. It is also preferable to use margins, because it is margins that drive the incumbents' behaviour in our model, as indicated through margins entering the first-order conditions for profit maximisation.

Our approach is therefore to use the incumbents' variable costs, c_j, to calculate base case and entry case margins, and ensure that the margin ratio is equalised between the unadjusted and adjusted scenarios. That is:

$$\frac{p_j^b - c_j}{p_j^o - c_j} = \frac{p_j^e - c_j}{p_j^a - c_j} \tag{15}$$

Solving this equation yields:

$$p_j^a = c_j + \frac{(p_j^e - c_j)(p_j^o - c_j)}{p_j^b - c_j} \tag{16}$$

We calculate the adjusted prices using this equation, and apply these adjusted prices in our calculation of incumbent profits in the entry case.

We similarly adjust prices for the entrant. We do not have base case or observed prices for the entrant; we only have the entrant's unadjusted prices in the entry case. As noted earlier, we calculate the entrant's unadjusted price in the entry case as 25% below the unweighted median unadjusted base case incumbent price in each market. Analogously, we calculate *adjusted* prices for the entrant as 25% below the *adjusted* base case prices of the incumbents. We use this adjusted price to calculate the entrant's profits in the entry case.

5.3 Calculation of profits

In the base case and entry case, we calculate (variable) profits for each incumbent duopolist d with supermarkets $k \in \mathcal{K}_d$ in a given market by:

$$\Pi_d = \sum_{k \in \mathcal{K}_d} (p_k^a - c_k) Q_k \tag{17}$$

As noted in the section above, we use adjusted prices to calculate profits to ensure our measures are realistic. We calculate variable profits for the entrant in the entry case similarly, again using adjusted prices.

5.4 Calculation of consumer surplus

Consumer surplus in the base case and the entry cases with and without the regulatory intervention is given by (see Appendix C for full derivation):

$$E[CS] = \sum_g \frac{M_g}{\alpha_g} \ln[\frac{\sum_{j=1}^J \exp(V_{jg})}{1 - s_{0g}}] \tag{18}$$

To calculate the change in consumer surplus from the base case to either entry case, we subtract base case consumer surplus off entry case consumer surplus, with consumer surplus calculated using this formula.

However, equation (18) assumes a fixed basket size despite changes in price between the base case and entry case. We therefore also include a correction to capture changes in welfare driven by a quantity response to changes in price. Individual households may face a change in price between the base and entry cases either because the price at the store where they shop changes or because they change the store where they shop. The change in surplus for a individual household due to a change in the quantity they purchase depends on the parameters of the basket size function and the prices they face in the two cases. For household i in income quintile g who faces (adjusted) base case price p_i^b and (adjusted) entry case price p_i^e, it is given by (see Appendix C for the derivation):

$$\Delta CS_{ig} = \theta_{1g}[p_i^e(\ln(p_i^b) - \ln(p_i^e)) + p_i^e - p_i^b] \tag{19}$$

The independence of irrelevant alternatives (IIA) property of the multinomial logit model means the only households that switch the store where they shop between the base and entry cases are those that shop at an incumbent store in the base case and switch to the new store in the entry case.[8] We thus calculate from the market shares generated by our model the number of households in each quintile that stay at each incumbent store and that switch from each incumbent store to the entrant store, apply the appropriate prices to (19) for each group of households, and sum over all households in a market to get the total correction to the change in consumer surplus.

5.5 Calculation of welfare

Welfare in a given market in the base case is the sum of profits of the incumbents and consumer surplus, and in the entry case also includes the profits of the entrant. In solving the static model, we assess how welfare in each market would change were the market to switch from the base case to an entry case (with or without the regulatory intervention). At this stage we do not aggregate over markets because we do not expect the entrant to enter all markets. We aggregate over all markets later, using the results of the dynamic model of entry.

[8]See, generally, Train, 2009 pp.45-47.

To calculate the welfare implications for New Zealand we sum the consumer surplus impacts and the profits to New Zealand owned firms. We exclude the profits for foreign-owned firms, which in this case is only Woolworths. We assume the entrant is New Zealand-owned. A standard approach in CBA is for only the benefits and costs to domestic consumers and producers to count (Boardman et al., 2018), which would exclude profits to foreign-owned firms. There are, however, arguments for why the profits of foreign-owned local firms might be included in CBA, such as where the inclusion of these profits (conceptually) provides for the compensation principle of CBA, where the loss of profits to foreign-owned firms are compensated by the benefits elsewhere (Johansson and de Rus, 2019). Also, New Zealand competition law jurisprudence finds that profits to foreign-owned firms can be a benefit to New Zealand if they create gains from trade and investment, but not if they reflect 'functionless monopoly rents'.[9] For present purposes, we exclude profits of foreign-owned firms from our main results, but present a sensitivity test with these profits included.

6 Static model results

This section shows how the optimal prices chosen by stores and the average prices faced by consumers change within a market when entry occurs. That is, it shows the difference between prices in the base case and prices in the entry case. Although we simulate two entry cases, with and without the regulatory intervention, prices in the two are identical because the regulatory intervention affects the entrant's costs only, and the entrant's prices are exogenous.

6.1 Markets served by the entrant

Of the 200 markets in our model, 39 have no stores in them, 37 have only one store in them, and 21 have more than one store but only one incumbent in them. As discussed earlier, we rule these markets out from entry, on the assumption that entry is unlikely to be viable. This leaves 103 potential markets that we allow the entrant to enter. These markets already contain multiple stores and have both incumbents operating in them.

6.2 Prices faced by consumers overall

Figure 5 shows the distribution across incumbent stores of the percentage decrease in price if entry occurs (omitting stores in markets we do not allow the entrant to enter), for our preferred specification. The price decreases fall between 0% and (approximately) 3%, with most in the range of 0% to 1%. The unweighted average price decrease in incumbent prices across all stores is 0.97% (with a 90% confidence interval of 0.70% to 1.28% across 500 runs of the model in which we allow all parameter values to vary randomly within their plausible ranges).

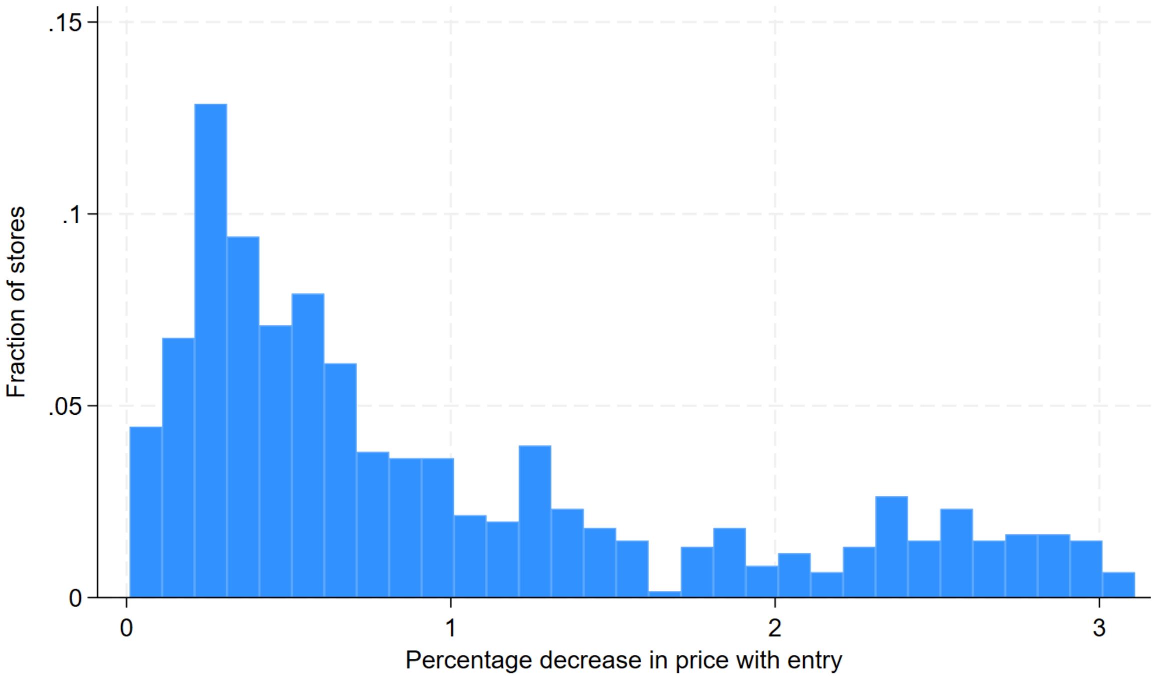
To put these numbers in context, the Commerce Commission considers a merger to substantially lessen competition if prices increase by at least 5%. Given the Commission found competition problems in the grocery sector (Commerce Commission, 2022), we might expect entry to decrease prices by at least 5%. However, the entrant is a hard discounter and competes only at the more price sensitive end of the market. As we show in the next section, price decreases for households in lower income quintiles are larger.

6.3 Prices faced by consumers by income quintile

In Figures 6, 7, 8, 9, and 10 we show the distribution of percentage decreases in average price faced by each income quintile. As we move from income quintile 1 through to 5, the distribution becomes compressed closer to zero. That is, those in higher income quintiles face smaller price

[9] *Telecom Corporation of New Zealand Ltd v Commerce Commission* [1991] 4 TCLR 473 (HC).

Figure 5: Distribution across incumbent stores of the percentage decrease in price when entry occurs



decreases. This is because those in higher income quintiles are less likely to shift to the hard discounter.

The price decreases faced by the income quintiles tend to be larger than the price decreases at the store level. This is because households experience price decreases both from store-level decreases in price and from switching to the lower-priced entrant stores.

7 Dynamic model set-up

The static model allows us to quantify the impact of entry in each market on optimal prices, quantities, incumbent and entrant profit, and consumer utility. However, the entrant may not consider all markets worth entering, and even among markets it plans to enter, it may not enter them all simultaneously. Delayed entry means the welfare effects of entry will also be delayed.

In this section we describe a dynamic model that predicts which markets the entrant will enter and when, with and without the regulatory intervention. From this we construct the pathways over time of welfare with and without the regulatory intervention, and use the difference between them at each point in time to estimate the net present benefit of the regulatory intervention.

We calculate net present value (NPV) over a period of ten years and use a discount rate of 8%.[10] Although New Zealand's population and GDP per capita are expected to grow over this period, we ignore growth beyond 2025. This means our results are conservative.

Entry in the dynamic model assumes other (non-labelling related) changes in the regulatory and market environment for supermarket competition make it profitable for the entrant. The Commerce Commission (Commerce Commission, 2022, p.189) found various barriers to entry

[10] This is the discount rate recommended by the Treasury for commercial proposals. See https://www.treasury.govt.nz/information-and-services/public-sector-leadership/guidance/reporting-financial/discount-rates

Figure 6: Distribution across markets of the percentage decrease in average price faced by income quintile 1 when entry occurs

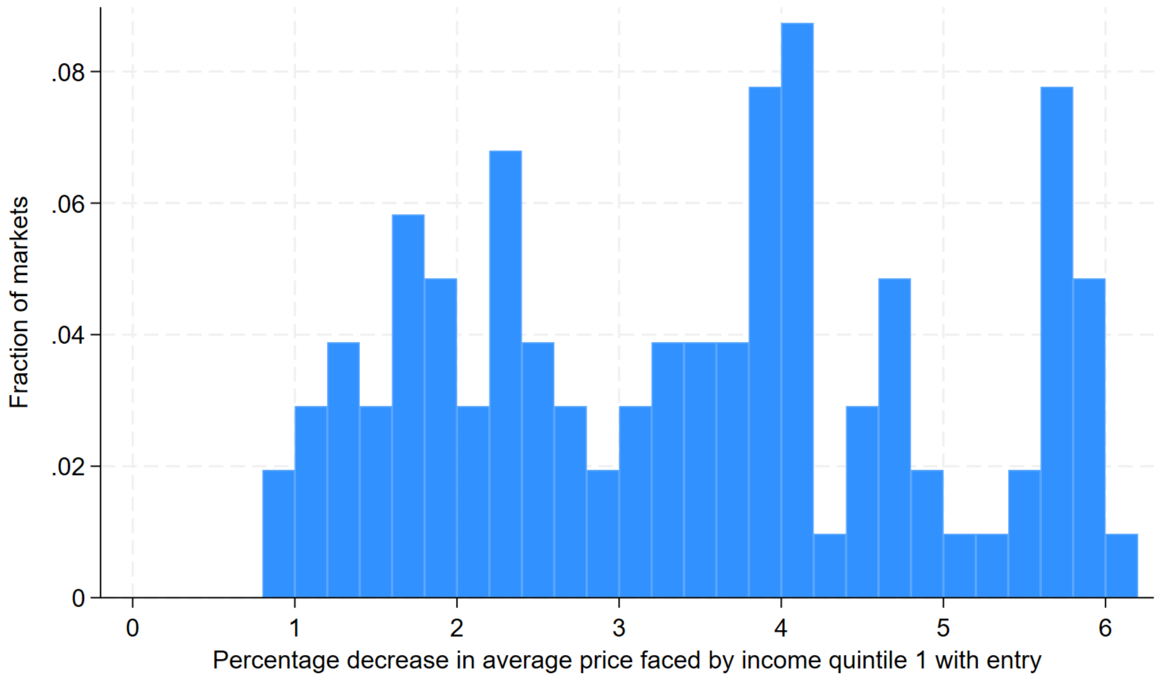


Figure 7: Distribution across markets of the percentage decrease in average price faced by income quintile 2 when entry occurs

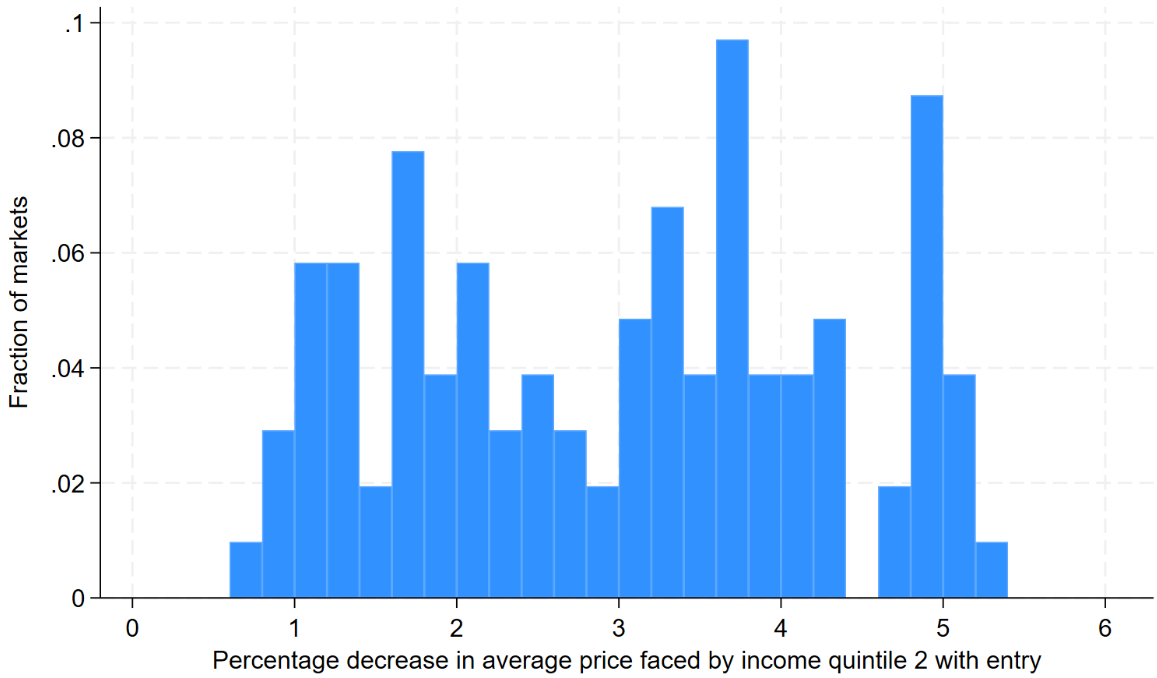


Figure 8: Distribution across markets of the percentage decrease in average price faced by income quintile 3 when entry occurs

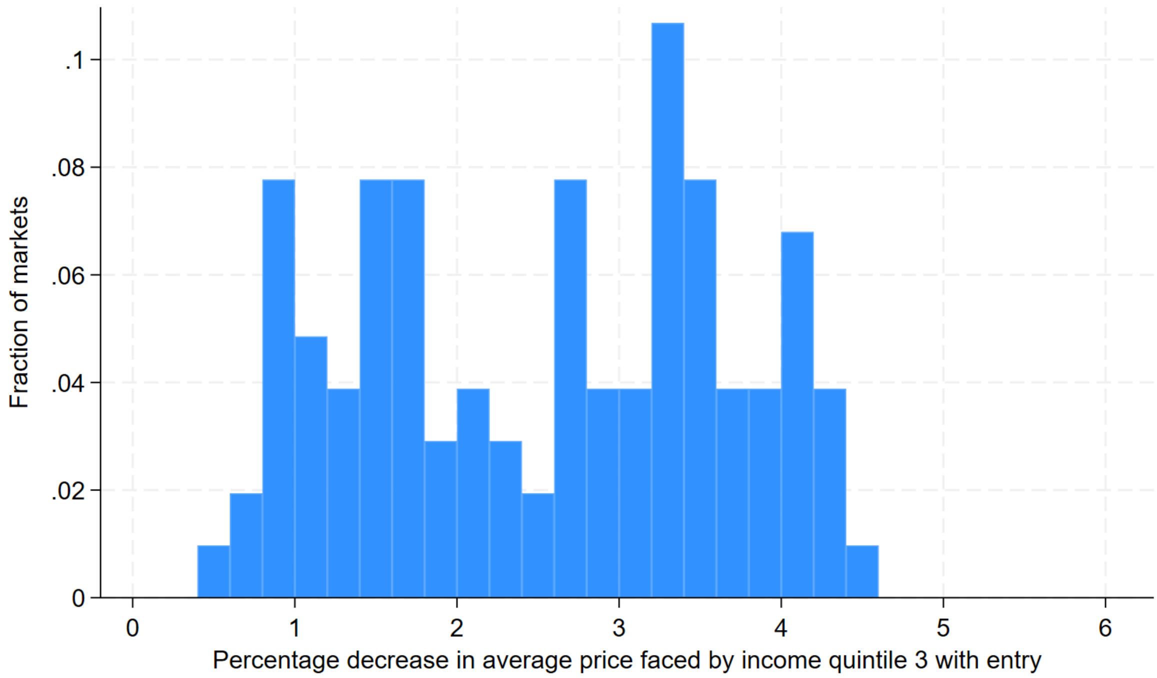


Figure 9: Distribution across markets of the percentage decrease in average price faced by income quintile 4 when entry occurs

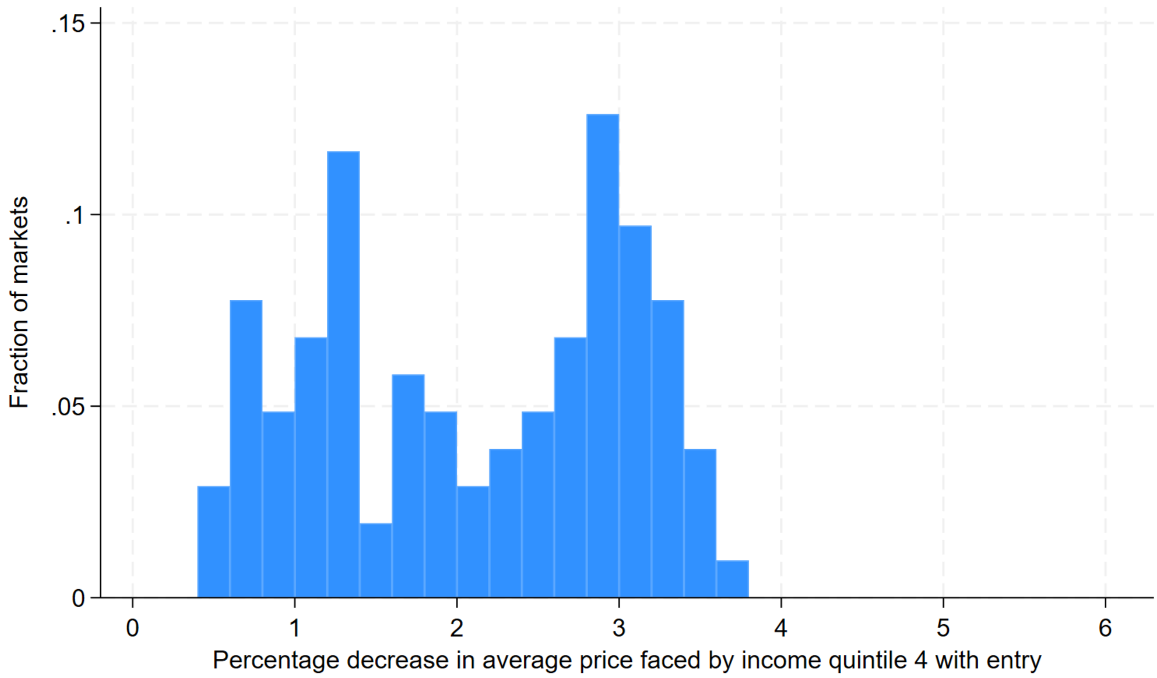
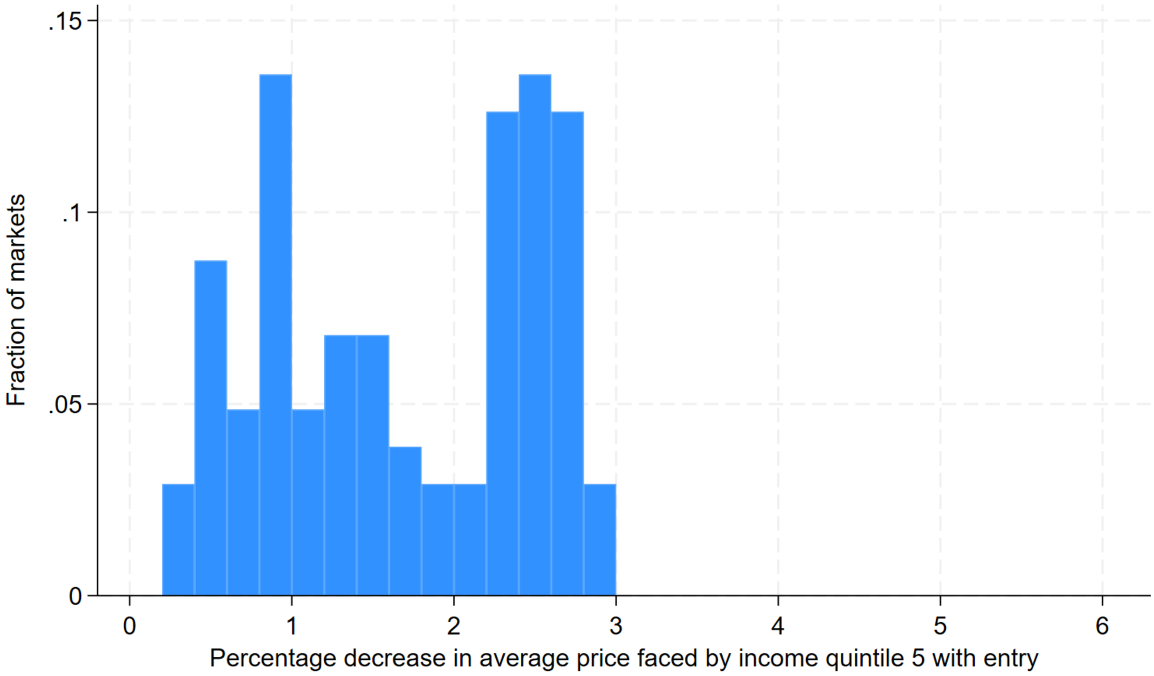


Figure 10: Distribution across markets of the percentage decrease in average price faced by income quintile 5 when entry occurs



in grocery retailing, including lack of suitable sites, planning laws, and lack of wholesale access to groceries. An implicit assumption underlying our analysis is that these entry barriers are reduced through other regulatory changes, facilitating entry to occur; other regulatory work is in progress in this regard.[11] If these changes are not extensive enough, there may be no entry in the static model regardless of the regulatory intervention in product labelling. This possibility is captured in our sensitivity analysis.

We impose the following process for entry to determine the markets that the entrant will enter and the speed of entry.

We do not allow the entrant to enter into a market where there is currently only a single store, or where one of the incumbents is a monopoly across all stores. On the one hand, we might expect the entrant to want to enter such markets, because this is where there will be monopoly profits and the strongest incentives to capture some of those profits. However, the lack of entry to date by other stores or the other duopolist suggests that there are constraints on entry, including the ability to support additional players. We assume these constraints outweigh any potential to capture monopoly profits, and thus the entrant would not enter these markets. Consistent with these constraints, the Commerce Commission found that scale was an important factor when considering entry, with a customer base of sufficient size important to ensure an entrant would earn enough return to justify its investment (Commerce Commission, 2022, paragraph 6.25).

In each market (excluding those single store/monopoly markets), we calculate the entrant's variable profit minus annual fixed costs, and determine the time it will take to earn back the one-off entry costs in each market. We rank markets by the time taken to earn back these one-off costs, and assume that the entrant will enter markets in order of fastest payback first.

We also impose a rule that if it takes more than 4 years for the entrant to recover the one-off

[11] See https://www.mbie.govt.nz/business-and-employment/business/competition-regulation-and-policy/supermarket-competition

costs of entry in a market, then it does not enter. We base the 4-year figure predominately off Cowling and Wilson, 2025, who analyse UK firms to find an average payback period (the time to fully recoup the initial investment cost) of 3.71 years. This does depend on firm size, with smaller firms having a payback period generally less than 3 years, and larger firms of around 4 years. Block, 1997 surveys US businesses and finds an average payback period of 2.81 years, although this is specifically for small businesses. Since we expect the entrant to be a relatively large business, we use a value of 4 years, but also vary this in sensitivity testing between 2 and 6 years.

For analytical tractability, we assume the cost of entering one market does not depend on which other markets the entrant is already in. In reality, we might expect the pattern of entry to focus on entering markets near where the entrant already is, for example, due to the logistics of delivering supplies from a single distribution centre's location.

We also assume the entrant enters each market with only one store. In this sense, our estimation of the benefits of the regulatory intervention is likely to be conservative because there are likely to be markets where a second entrant store would be sufficiently profitable and socially beneficial, but where we do not model a second store as occurring.

If any markets meet the profitability criteria for entry, in month 1 the entrant enters the highest ranking market and incurs a one-off entry cost. We assume annual fixed costs reach their full value immediately but variable profits scale up linearly to the full value over the first two years (although we sensitivity test this over a range of 6 months to 3 years).

After the entrant has accumulated profit in the first market to pay off 50% of its one-off cost, it opens a new store in the next most attractive market (as ranked by payback period). We use 50% as our preferred parameter, but vary this between 25% and 75%. We are not aware of any literature to provide a value for this parameter, although the literature does support the proposition that it will be less than 100% (i.e., entry occurs in new markets even when the entrant is still recovering the costs of earlier entry). In particular, Chenarides et al., 2024 model firm entry based on expected profits, entry costs, and competition, and show that entry occurs if expected present value of future profits exceeds entry costs, even if previous stores have not fully recovered their entry costs. Nishida and Yang, 2015 model retail chain expansion as a dynamic process, with expansion decisions based on a forward-looking analysis, with no assumption that chains wait for full cost recovery before opening new stores.

This assumption means the dynamic model predicts entry will occur slowly initially, but speed up as the number of existing entrant stores increases. Real life dynamics are also supportive of this approach. For example, an entrant will build its reputation and brand recognition over time, will learn about how its model operates in New Zealand, and may tend to focus on its managerial resources in the early days, limiting its ability to open too many stores too quickly. This may mean it starts out slowly, but builds out its stores more quickly as it becomes more established in the country.

8 Dynamic model results

In this section we describe the results of the dynamic model. For each set of parameter values, we simulate entry over ten years with and without the regulatory intervention, and take the difference in outcomes between the two scenarios as the impact of the regulatory intervention.

We run the model varying parameters in three different ways. First, we use our preferred values for each parameter. This yields our best estimates of the impact of the regulatory intervention. Second, we run it 500 times allowing all parameter values at once to vary randomly within their plausible ranges. This gives a distribution of results, from which we construct confidence intervals for the main values of interest. Third, we run it varying one parameter at a time to the upper and lower extremes of its plausible values, holding all other parameters at their preferred values. This demonstrates the sensitivity of our results to each assumption about parameter values.

Table 1 shows for each parameter in our model the preferred value and the range over which we allow it to vary. Some of these parameters, particularly those relating to values that vary by income quintile, are expressed as multipliers. In such cases we choose a vector that gives the central value for each income quintile, and vary the values across runs by multiplying all the central values by the same run-specific multiplier. The preferred value for such multipliers is always 1. This approach keeps the number of varying parameters manageable and ensures the relationship between the income quintiles is preserved across our different runs.

The central values for ϵ, the own price elasticity of store choice, are -2.1, -1.925, -1.75, -1.575, and -1.4 for income quintiles 1 to 5 respectively. We vary these using multipliers that range from 0.8 to 1.2.

The central values for ζ, the elasticity of store choice with respect to SKUs, are 0.11, 0.12, 0.13, 0.14, and 0.15 for income quintiles 1 to 5 respectively. We similarly vary these using multipliers from 0.8 to 1.2.

The central values for γ, the coefficient on customer experience in the utility function, are 0.25, 0.34, 0.43, 0.52, and 0.60 for income quintiles 1 to 5 respectively. We again use multipliers from 0.8 to 1.2.

The central values for η, the price elasticity of basket size, are -1.0, -0.825, -0.65, -0.475, and -0.3 for income quintiles 1 to 5 respectively. We again use multipliers from 0.8 to 1.2.

We assume the entrant's variable costs are a certain fraction lower than the national average of variable costs for the incumbent, where the fraction depends on how urban the market is. For central values, we use a 0.2 discount in major urban areas, a 0.15 discount in large urban areas, and a 0.1 discount everywhere else (so entrant variable costs range from 80% to 90% of incumbent variable costs). We vary the entrant's variable costs across runs of the model using a multiplier for the cost discount that ranges from 0.8 to 1.2.

We assume the entrant's annual fixed costs vary with the store size and how urban the market is. The base annual fixed cost of the entrant operating a store is calculated as the 'coefficient on SKUs in entrant annual fixed cost function' ($162.85 in the preferred specification) multiplied by the store's number of SKUs. Annual fixed costs in different types of area are calculated relative to this base annual fixed cost. The second parameter that defines annual fixed cost is the 'increment in the multiplier in the entrant annual fixed cost function between adjacent urbanness categories', which has a preferred value of 0.25. The annual fixed costs in different areas are as follows:

1. Base annual fixed cost multiplied by (1 plus twice the increment) in major urban areas
2. Base annual fixed cost multiplied by (1 plus the increment) in large urban areas
3. Base annual fixed cost in medium urban areas
4. Base annual fixed cost multiplied by (1 minus the increment) in small urban areas
5. Base annual fixed cost multiplied by (1 minus twice the increment) in rural settlements.

8.1 Preferred specification and distribution of results

This section describes the results from our preferred specification of the dynamic model and how they vary across our runs that randomly vary the parameters.

8.1.1 Markets served by the entrant

Our dynamic model captures the fact the entrant may not consider all markets worth entering, and even among markets it plans to enter, it may not enter them all simultaneously. The impact of the regulatory intervention is the difference in entry between the scenarios with and

Table 1: Preferred parameter values and sensitivity bounds

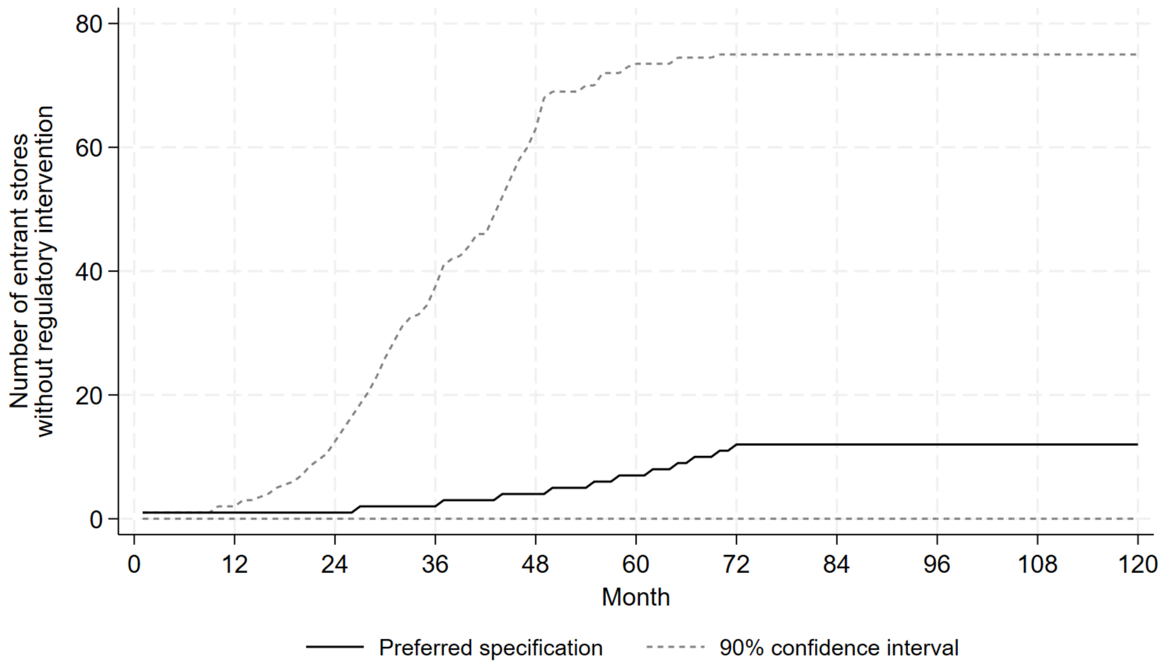
	Preferred value	Lower bound	Upper bound
Multiplier for ϵ, store choice own price elasticity	1	0.8	1.2
Multiplier for ζ, elasticity of store choice with respect to SKUs	1	0.8	1.2
Multiplier for γ, sensitivity of utility to customer experience	1	0.8	1.2
Multiplier for η, price elasticity of basket size	1	0.8	1.2
Entrant's price discount relative to incumbent average	0.25	0.15	0.35
Multiplier for entrant's cost discount relative to central values	1	0.8	1.2
Customer experience value for entrant	0.05	0	0.10
Standard SKUs that entrant enters with	2800	1600	4000
One-off cost per SKU of entrant opening store ($)	878.90	206.80	1551.00
Coefficient on SKUs in entrant annual fixed cost function ($ per annum)	162.85	46.53	279.18
Increment in the multiplier in the entrant annual fixed cost function between adjacent urbanness categories	0.25	0.125	0.5
Months for new store to reach full capacity	24	6	36
Maximum years to make back entry cost above which entry does not occur	4	2	6
Fraction of one-off entry costs covered by accumulated profit before more entry occurs	0.5	0.25	0.75

without the regulatory intervention. In this section we first discuss the extent of entry without regulatory intervention, then consider how this changes with the intervention.

While 103 possible markets could be entered, in our preferred specification without the regulatory intervention the entrant enters a total of 12 markets over 10 years (with a 90% confidence interval of zero to 75 markets). Equivalently, it opens 12 stores over this period, since we assume it only enters with one store per market. Across the 500 random runs where the parameter values vary, 34.8% of runs have no entry absent regulatory intervention.

Figure 11 plots the number of entrant stores over time in the situation without the regulatory intervention. It presents the trajectory in the preferred specification and the 90 percent confidence interval over our random runs. It shows in the preferred specification entry begins slowly; the second store is not opened until the third year. With some parameter combinations the number of stores climbs rapidly after about a year. At the 95th percentile as in the preferred specification, the number of stores plateaus after about 6 years.

Figure 11: Number of entrant stores each month without the regulatory intervention



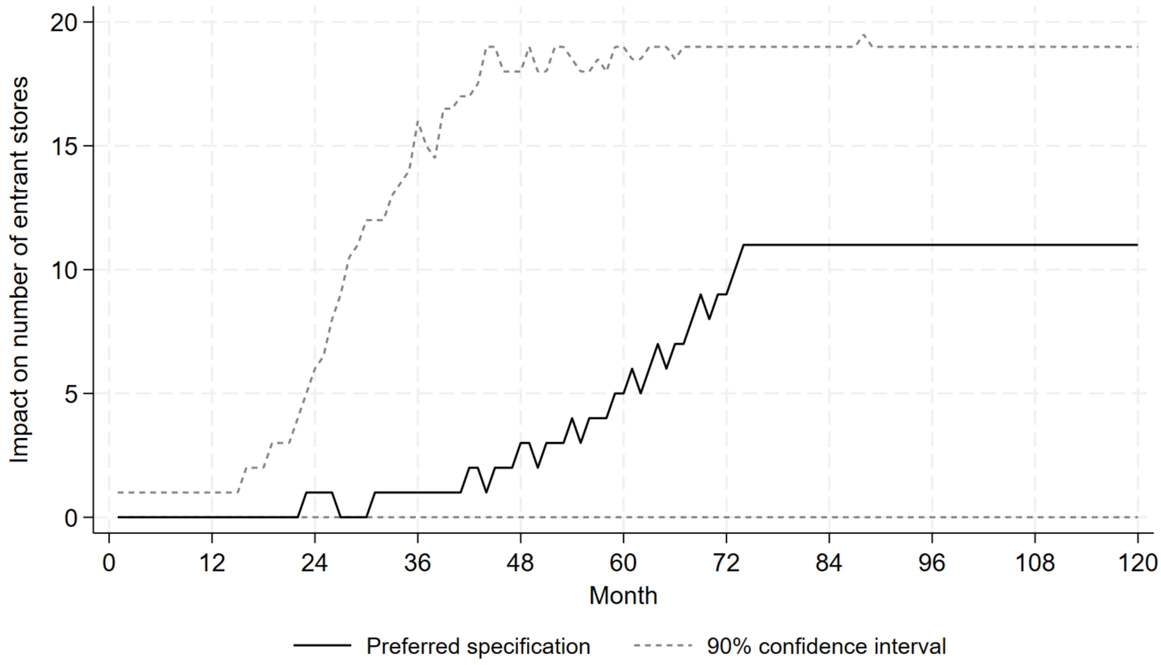
In our preferred specification, the regulatory intervention causes the entrant to enter an *additional* 11 markets over 10 years (with a 90% confidence interval of zero to 19 markets). Across the 500 random runs, 19.2% of the runs have no entry even in the regulatory intervention case.

Figure 12 plots the path over time of the impact of the regulatory intervention on the monthly number of markets entered. The entrant enters one additional market as a result of the regulatory intervention within the first two years, and this ramps up over time until it reaches the 11 additional markets after about six years.

In most of the random runs, the entrant exhausts the markets that are worth entering according to our entry rules within the 10-year period we model. The total number of markets ultimately entered is therefore driven by the number of markets that are attractive to enter, not how long the entrant has to accumulate profits to help cover its entry costs.

A total of 1,833,266 households live in New Zealand. After 10 years, 467,159 of these live in

Figure 12: Impact of the regulatory intervention on the number of entrant stores each month



a market served by the entrant in our preferred specification without the regulatory intervention (with a 90% confidence interval of zero to 1,500,157). The regulatory intervention results in an *additional* 365,515 households living in a market served by the entrant after 10 years (90% confidence interval of zero to 433,848). Figure 13 plots the monthly path of the additional households living in a market served by the entrant due to the regulatory intervention.

8.1.2 Incumbent variable profits

The regulatory intervention causes the entrant to enter more markets, drawing households away from the incumbents' stores and therefore decreasing their variable profits. The regulatory intervention results in Woolworths's annual variable profits falling by $12.69 million (90% confidence interval of zero to $17.14 million) after 10 years, and Foodstuffs's annual variable profits falling by $11.48 million (90% confidence interval of zero to $21.37 million). Figures 14 and 15 show the impact of the regulatory intervention on the variable profits each month of Woolworths and Foodstuffs respectively. Even though the entrant opens its final store after approximately six years (from Figure 12), Woolworths's and Foodstuffs's variable profits continue to fall for another two years because we assume households take time to adjust their shopping habits.

In NPV terms (discounting using an 8% discount rate), the regulatory intervention results in Woolworths's variable profits falling by $33.01 million (90% confidence interval of zero to $62.83 million) and Foodstuffs's variable profits falling by $28.75 million (90% confidence interval of zero to $81.13 million).

8.1.3 Entrant profits

In our preferred specification, without the regulatory intervention the entrant's profits after 10 years are $14.17 million per annum (90% confidence interval of zero to $76.70 million). The regulatory intervention causes the entrant to enter an additional 11 markets, and this increases

Figure 13: Impact of the regulatory intervention on the number of households living in markets served by the entrant each month

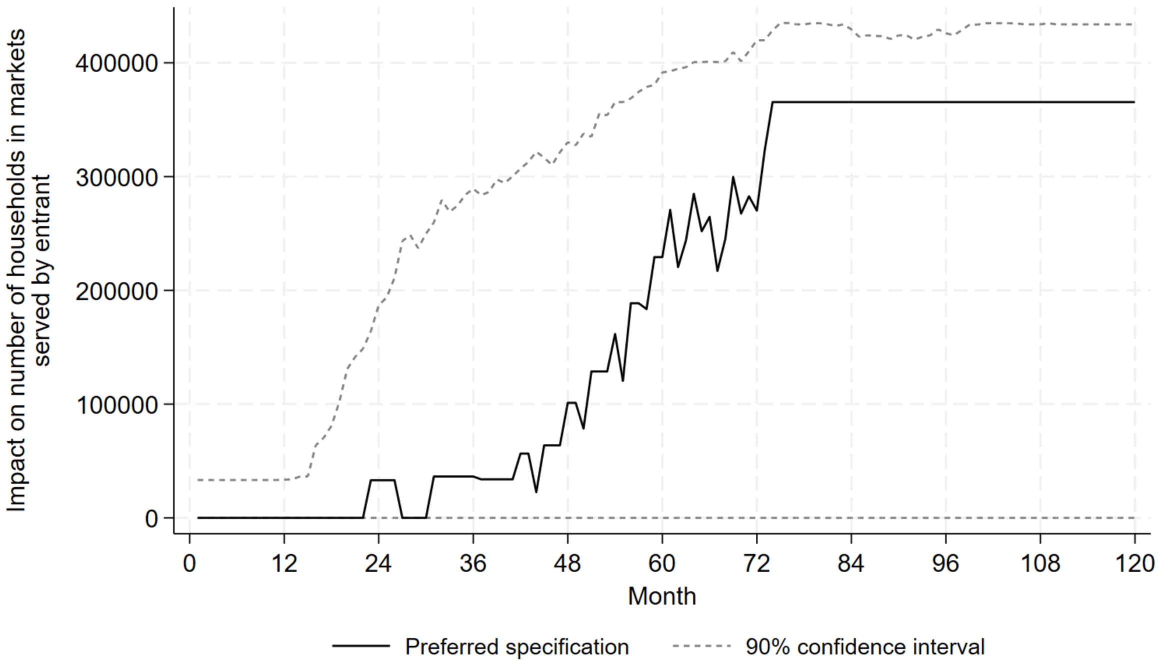


Figure 14: Impact of the regulatory intervention on Woolworths's variable profits each month

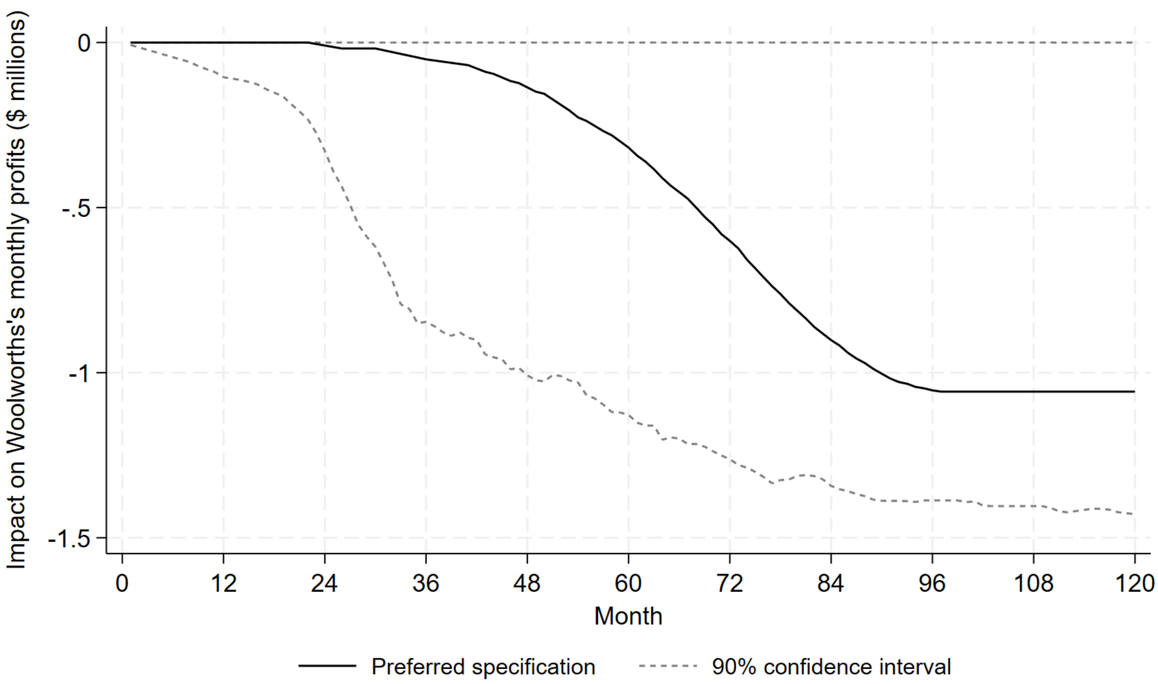
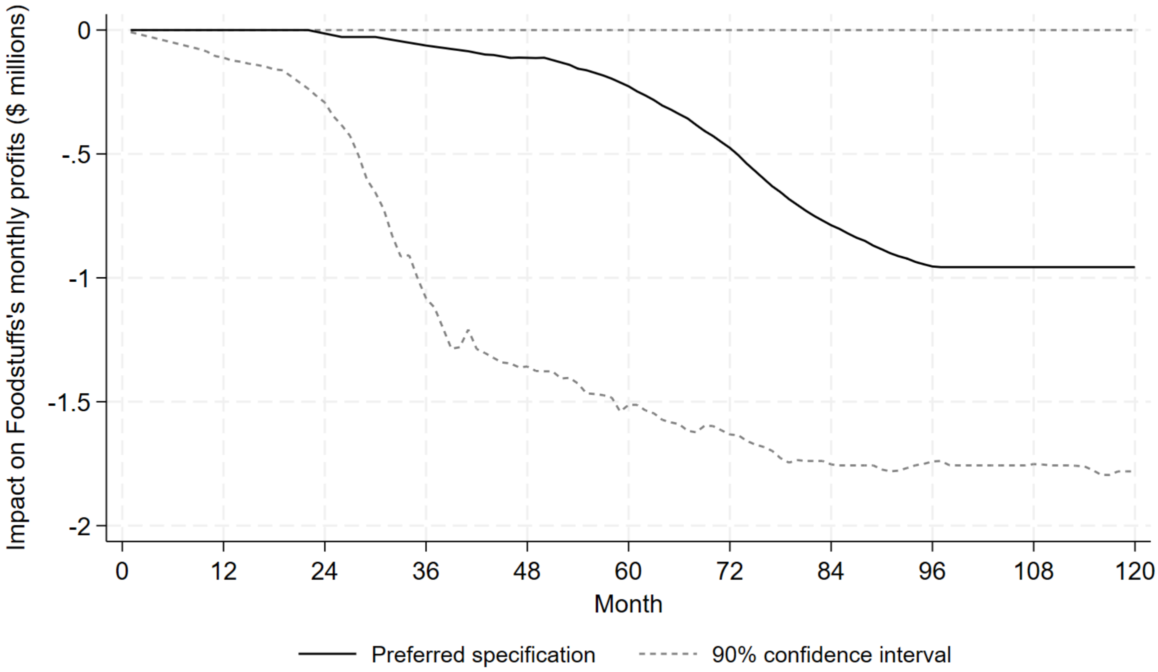


Figure 15: Impact of the regulatory intervention on Foodstuffs's variable profits each month



its profit after 10 years by $15.72 million per annum (90% confidence interval of zero to $27.18 million). These annual profits are calculated as variable profits minus annual fixed costs. We exclude one-off entry costs here because their lumpiness creates challenges for interpretation. However, our NPV results reported below include one-off entry costs and thus are appropriate for use in calculating overall benefits to society.

In Figure 16 we show the entrant's profits (excluding entry costs) without the regulatory intervention in each month over 10 years and in Figure 17 we show how the regulatory intervention affects these profits.

In NPV terms, the regulatory intervention results in the entrant's profits (variable profits less annual fixed costs and one-off entry costs) increasing by $20.83 million (with a 90% confidence interval of zero to $108.24 million).

8.1.4 Consumer surplus

The effect of the regulatory intervention on consumer surplus after 10 years is $66.64 million per annum (90% confidence interval of zero to $103.10 million). Figure 18 shows the path over time of the impact of the regulatory intervention on monthly consumer surplus. In our preferred specification, the impact on consumer surplus increases above zero in year two, after the entrant has entered an additional market as a result of the regulatory intervention. From there it increases relatively smoothly through to year eight. The regulatory intervention increases consumer surplus by $173.58 million in NPV terms over this 10-year period (90% confidence interval of zero to $423.59 million).

After 10 years, the average consumer surplus benefit per household in each additional market served by the entrant due to the regulatory intervention is $182 per annum (with a 90% confidence interval of $158 to $488).

Figure 16: Entrant's profits each month without the regulatory intervention (excluding one-off costs of entry)

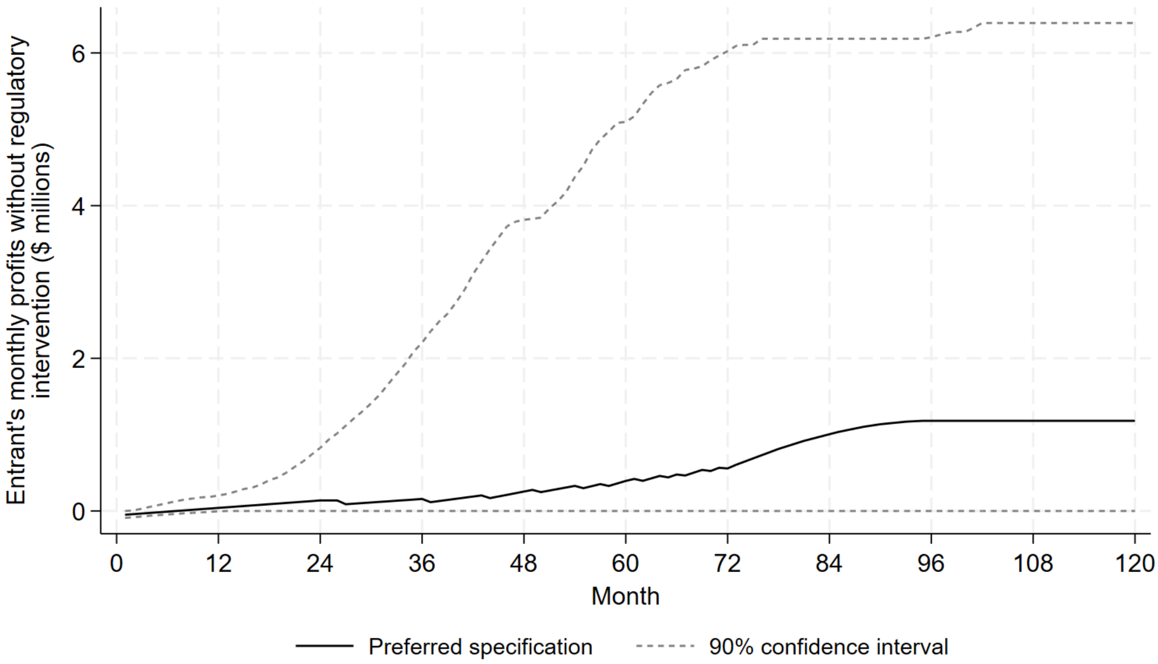


Figure 17: Impact of the regulatory intervention on entrant's profits each month (excluding one-off costs of entry)

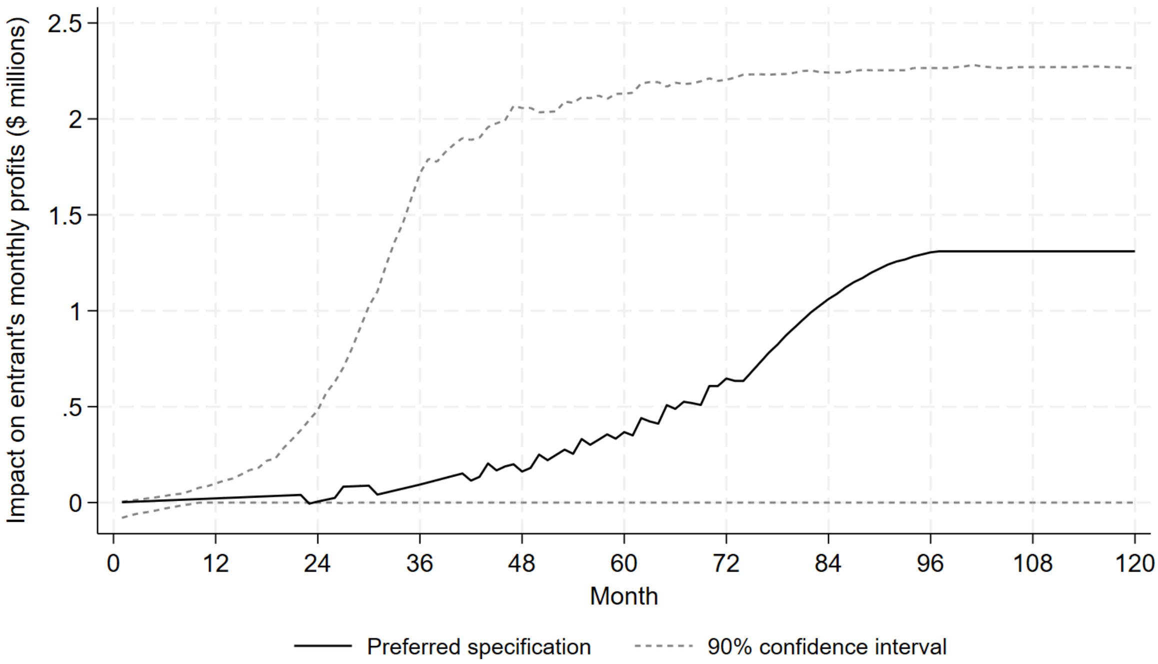
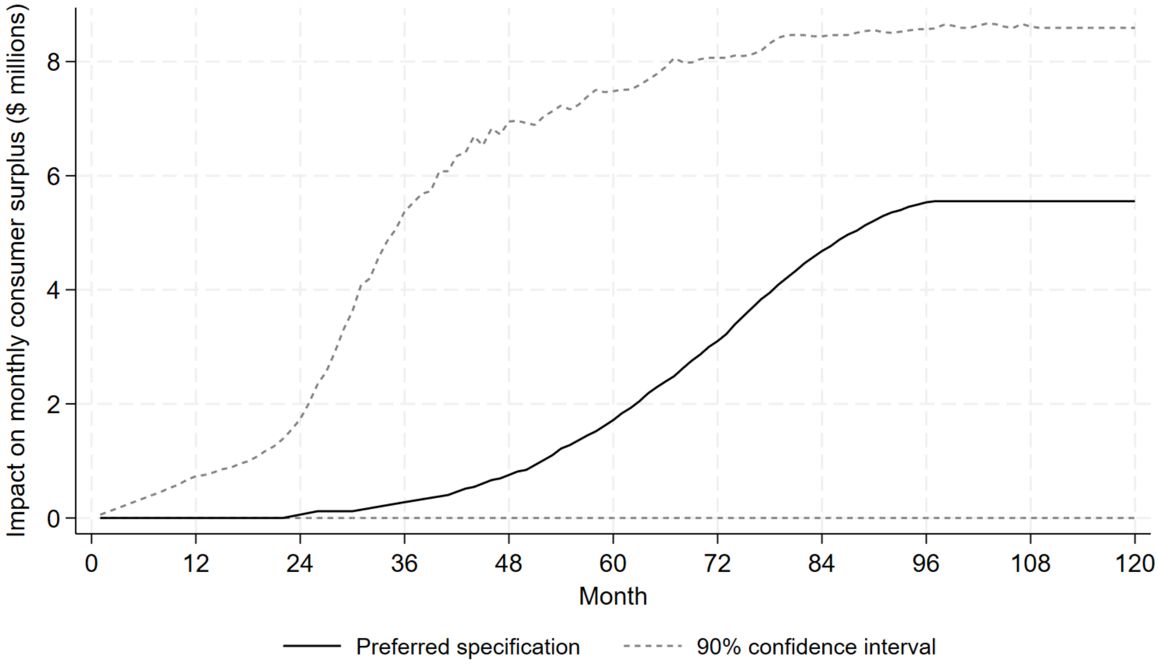


Figure 18: Impact of the regulatory intervention on consumer surplus each month



8.1.5 Social welfare

Figure 19 shows the monthly impact of the entrant on domestic social welfare over a 10-year period in the scenario without the regulatory intervention. Domestic social welfare is defined in this figure as the sum of Foodstuffs's variable profits, the entrant's profits (excluding one-off entry costs), and consumer surplus. We exclude the impact on Woolworths's variable profits because it is foreign owned.

Even without the regulatory intervention, our preferred scenario estimates a benefit to social welfare of nearly $8 million per month by the end of 10 years as a result of entry by the hard discounter. This value is sensitive to assumptions about parameters. The 95th percentile across our random runs is $28 million and the 5th percentile is zero.

Figure 20 shows how the regulatory intervention affects domestic social welfare, defined as in the figure above. The change in domestic social welfare from the regulatory intervention after 10 years is $70.88 million per annum, excluding one-off entry costs (90% confidence interval of zero to $102.24 million).

In NPV terms (where we now include one-off entry costs), the regulatory intervention increases domestic welfare by $165.66 million (90% confidence interval of zero to $403.63 million). When Woolworths's profits are included, the regulatory intervention increases domestic welfare by $132.65 million in NPV (90% confidence interval of zero to $347.63 million).

8.2 Sensitivity of results to each parameter

In this section we show the sensitivity of our results to each individual parameter. Table 2 shows the impact on our main results of varying each parameter in our model to the upper and lower bounds of its range while holding all other parameters fixed at their preferred values.

Many of the parameters have limited impact on the estimated effect of the regulatory intervention. In particular, varying each of these parameters to the ends of its range never moves the NPV of the regulatory intervention's effect on social welfare by more than 10 percent:

Figure 19: Impact of entry on domestic social welfare each month without the regulatory intervention

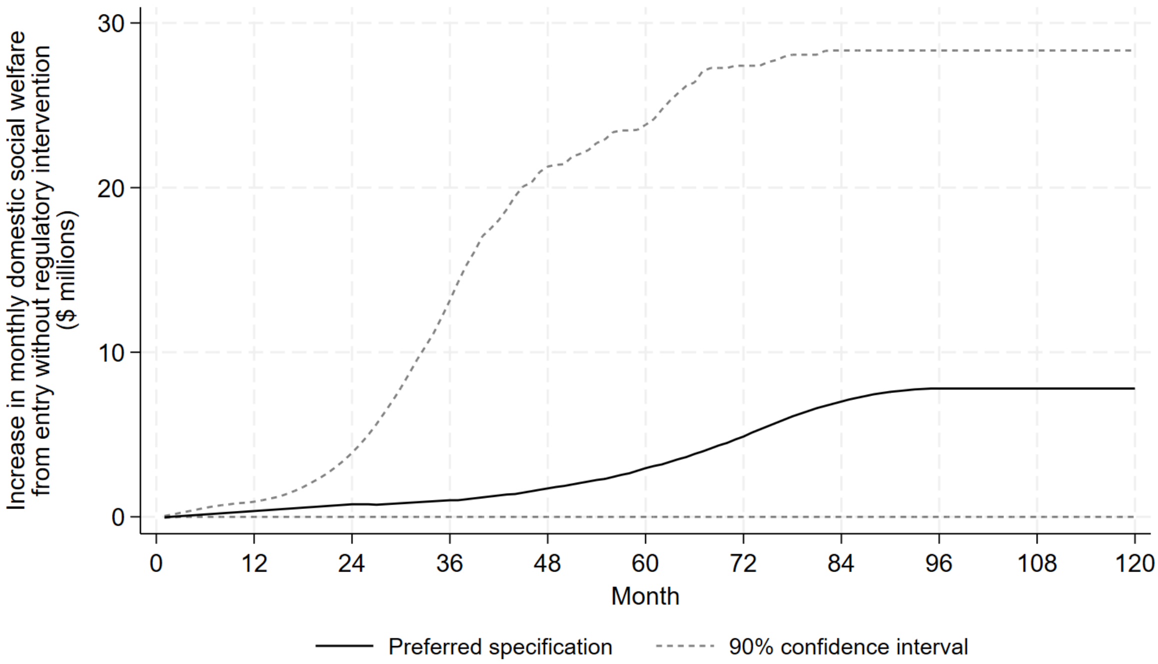


Figure 20: Impact of the regulatory intervention on domestic social welfare each month

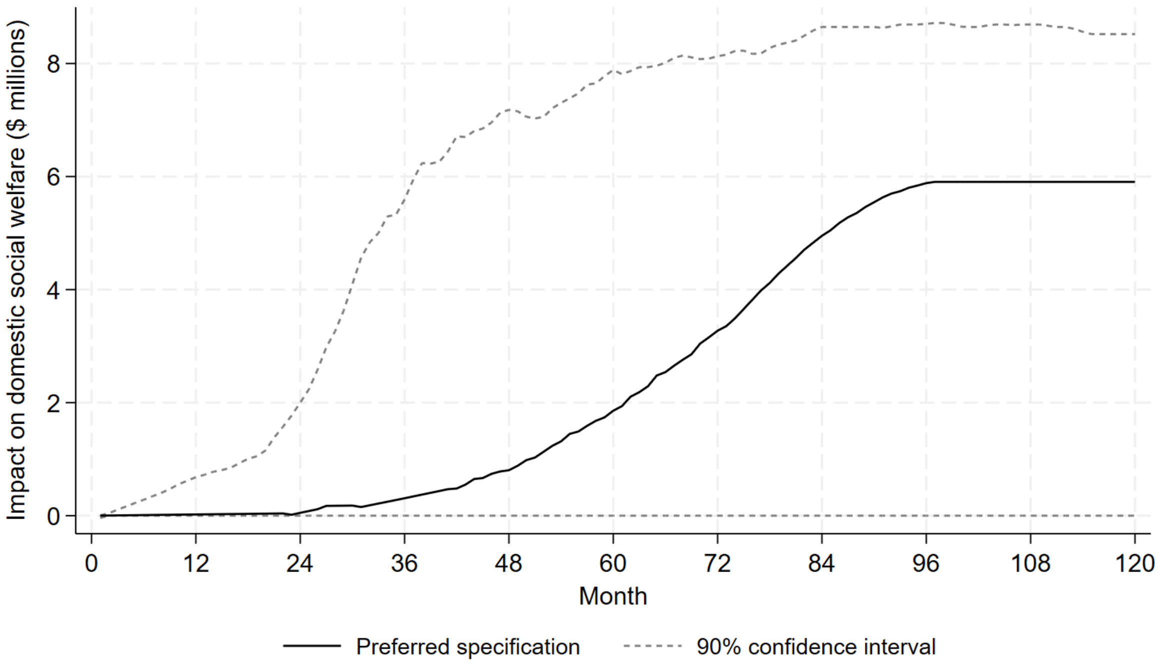


Table 2: Sensitivity of results to variations in individual parameters

Parameter being varied	Parameter value	Impact of regulatory intervention on: Number of entrant stores after 10 years	NPV of consumer surplus ($ m)	NPV of entrant's profits ($ m)	NPV of Foodstuffs's profits ($ m)	NPV of Woolworths's profits ($ m)	NPV of domestic social welfare ($ m)
Preferred specification		**11**	**173.58**	**20.83**	**-28.75**	**-33.01**	**165.66**
Multiplier for ϵ, store choice own price elasticity	0.8	9	162.74	16.76	-20.63	-25.05	158.87
	1.2	10	152.95	25.71	-30.06	-34.56	148.60
Multiplier for ζ, elasticity of store choice w.r.t SKUs	0.8	11	183.22	21.16	-29.12	-33.29	175.27
	1.2	11	164.54	20.37	-28.51	-32.72	156.39
Multiplier for γ, utility sensitivity to experience	0.8	11	184.93	21.32	-29.25	-33.45	177.00
	1.2	11	163.62	20.33	-28.49	-32.70	155.46
Multiplier for η, price elasticity of basket size	0.8	11	166.47	18.53	-29.92	-34.75	155.08
	1.2	10	168.77	24.18	-25.93	-29.98	167.03
Entrant price disc. relative to incumbent average	0.15	9	129.38	49.32	-32.13	-23.02	146.57
	0.35	0	0.00	0.00	0.00	0.00	0.00
Multiplier for entrant's cost discount	0.8	8	159.42	12.86	-21.72	-30.36	150.56
	1.2	8	158.47	34.96	-29.42	-27.71	164.00
Customer experience value for entrant	0	11	170.22	20.79	-28.73	-32.80	162.28
	0.10	11	176.40	20.92	-28.79	-33.08	168.53
Standard SKUs that entrant enters with	1600	18	300.08	58.96	-69.56	-45.69	289.48
	4000	6	125.28	6.51	-17.08	-22.77	114.71
One-off cost per SKU of entrant opening store ($)	206.8	21	380.59	62.89	-76.94	-53.62	366.54
	1551	7	140.95	8.59	-20.60	-25.77	128.95
Coeff. on SKUs in entrant annual fixed cost function	46.53	14	244.56	47.75	-51.75	-37.23	240.56
	279.18	8	134.68	5.13	-19.42	-24.44	120.40
Urbanness multiplier increment[a]	0.125	10	168.04	26.91	-28.32	-31.65	166.63
	0.5	8	136.98	13.80	-21.77	-25.78	129.02
Months for new store to reach full capacity	6	15	404.56	54.84	-76.46	-71.86	382.95
	36	6	82.07	11.63	-12.56	-15.70	81.14
Entry cost maximum years[b]	2	0	0.00	0.00	0.00	0.00	0.00
	6	15	210.35	17.79	-40.90	-34.93	187.23
Fraction of entry costs covered[c]	0.25	11	228.20	30.59	-38.36	-43.42	220.42
	0.75	11	129.55	13.38	-20.96	-24.65	121.96

[a] Increment in multiplier in entrant annual fixed cost function between adjacent urbanness categories.
[b] Maximum years to make back entry cost above which entry does not occur.
[c] Fraction of one-off entry costs covered by accumulated profit before more entry occurs.

1. The multiplier for ϵ, store choice own price elasticity
2. The multiplier for ζ, elasticity of store choice with respect to SKUs
3. The multiplier for γ, the sensitivity of utility to customer experience
4. The multiplier for η, price elasticity of basket size
5. The multiplier for the entrant's cost discount relative to its central values
6. The customer experience value for the entrant.

Other parameters shift the results more. The extent to which the entrant sets its prices below incumbent prices has a strong and non-monotonic effect on the social welfare impact of the regulatory intervention. A low discount results in substantially higher profits for the entrant relative to our preferred specification, but lower gains for consumer surplus. On balance, the benefits for social welfare are substantially lower. A high discount, however, makes it insufficiently profitable for the entrant to enter any markets even with the regulatory intervention, leading to the regulatory intervention having zero benefit.

The standard size of an entrant store in terms of SKUs also has a strong impact. Smaller stores result in the entrant entering more markets, earning higher profit, and providing greater consumer surplus benefits. Decreasing store size from 2800 SKUs to 1600 SKUs nearly triples the regulatory impact on the NPV of the entrant's profits and increases consumer surplus from \$174m to \$300m (an over 70 percent increase). The overall effect is a 75 percent increase in the NPV of the regulatory impact on social welfare (from \$166m to \$289m).

Results are also sensitive to the one-off cost of the entrant opening a new store. Extreme values of this parameter vary the regulatory impact on the number of stores opened from 7 to 21 (relative to 11 in the preferred specification) and vary the regulatory impact on social welfare from \$166m to \$129m (22 percent lower than in the preferred specification) and \$367 (121 percent higher).

The extent to which the entrant's annual fixed costs increase with SKUs also has a sizeable impact. At the lowest value of this parameter, the regulatory intervention's impact on social welfare is 45 percent higher than in the preferred specification (\$241m compared to \$166m); at its highest value, it is 28 percent lower (\$120m compared to \$166m). The extent to which annual fixed costs are higher in more urban areas also matters non-trivially. Weakening this relationship from its preferred strength has little impact on the effect of the regulatory intervention on social welfare, but strengthening it decreases the effect by 22 percent (social welfare falls to \$129m).

The speed at which a new entrant store reaches full capacity has very strong effects on the impact of the regulatory intervention. Decreasing this value from 2 years to 6 months more than doubles the NPV of the social welfare benefit from the regulatory intervention, whereas increasing it to three years more than halves the social welfare benefit.

The maximum length of time the entrant allows to make back the one-off cost of entry before it decides a market is not worth entering matters particularly on the downside. Increasing this parameter from 4 years to 6 years increases the additional markets entered due to the regulatory intervention from 11 to 15 and increases the impact on the NPV of social welfare by 13 percent (to \$187m); decreasing it to 2 years means no markets are worth entering regardless of regulation, and decreases the effect on social welfare to zero.

Varying the fraction of one-off entry costs that must be covered by accumulated profit before the entrant enters the next market does not affect the number of markets ultimately entered either with or without the regulatory intervention, but affects the speed of opening new stores and thus modestly affects the regulatory impact on the NPV of social welfare.

9 Conclusions

In this report, we estimate the impact of a regulatory intervention that provides a hypothetical hard discounter entrant to the New Zealand supermarket sector with relief from relabelling costs, enabling them to open more stores across the country more quickly. We find such a regulatory intervention could facilitate the entrant opening an additional 11 stores in its first 10 years of operation, resulting in an increase in domestic social welfare of $166 million in net present value over 10 years.

These findings have considerable uncertainty associated with them and, although rigorous, are reliant on a collection of assumptions and simplifications of real world dynamics. By varying parameter values in our model, we estimate a 90 percent confidence interval for the NPV of the increase in domestic social welfare of zero to $404 million. Some plausible combinations of parameter values mean it would not be worthwhile for an entrant to open any stores even with the regulatory intervention; this would result in zero benefit from the regulatory intervention. Nonetheless, our preferred parameter values suggest the regulatory intervention could have a sizeable net benefit.

We assume the regulatory intervention is done in a way that does not compromise consumer access to the information they require about the products they are purchasing; if the intervention were to impose a cost on consumers, this cost should be deducted from the net benefit we estimate.

Due to the limitations of this analysis, it should not be taken as a complete characterisation of the dynamics of supermarket competition in New Zealand. Rather, it should be interpreted as a conditional assessment of how reduced costs for a supermarket entrant could lead to increased competition in this sector and improved social welfare.

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Appendix A Static model set-up

A.1 Base case model

In the base case, we model competition between two incumbent supermarket firms in a market m. The remainder of our analysis applies to each market, and therefore to simplify the notation we omit the market subscript m. Each incumbent potentially owns multiple stores in a given market, indexed by $j = 1, 2, ..., J$ for a total of J stores. We estimate a multinomial logit model of discrete choice, in which households choose at which store to shop. Households are grouped by income quintile g, with utility for household i in income group g choosing store j given by:

$$U_{ijg} = -\alpha_g \, b_g \, p_j + \beta_g \, \ln A_j + \gamma_g \, X_j + \xi_{ijg} \tag{A1}$$

where p_j is price per item, A_j is assortment, and X_j is store customer experience. In our specification, price and experience enter the utility function linearly, while assortment enters in log form to reflect diminishing marginal utility from variety. The parameter b_g is the basket parameter, an exogenous measure of the number of items purchased in the shopping basket for a household in income quintile g, such that $b_g p_j$ measures the price for the basket. The parameter b_g is constant across markets. This utility function is often referred to as conditional utility, since it is conditional on the household choosing store j. However, we will continue to refer to it as utility for succinctness.

The parameters in equation (A1) to be estimated are the sensitivity of utility to basket price, α_g, assortment, β_g, and experience, γ_g. These parameters are constant across markets. The error term ξ_{ijg} captures unobserved factors that influence store choice, such as proximity to work, or habit. It is assumed to be independent and identically distributed (i.i.d) and Type I extreme value distributed, allowing us to use the multinomial logit model to reflect a household's store choice.

We denote the deterministic component of utility (equation (A1)) by V_{jg}. Here we omit the i subscript because the deterministic part of utility varies only at the income quintile-store level. That is,

$$V_{jg} = -\alpha_g b_g p_j + \beta_g \ln A_j + \gamma_g X_j \tag{A2}$$

We denote $j = 0$ as the outside option, which gives utility for household i in income quintile g of $U_{i0g} = V_{0g} + \xi_{i0g}$.

The utility function given in equation (A1) is additively separable, a common functional assumption used in the economics literature for analysing competition with differentiated products (e.g., Berry et al., 1995; Nevo, 2000).

Following Train, 2009 (p.51), application of the logit model gives the following share of households within income quintile g choosing store j:

$$s_{jg} = \frac{\exp(V_{jg})}{\sum_{j=0}^{J} \exp(V_{jg})} \tag{A3}$$

where in the denominator we sum over all the incumbents' stores J in the market and the outside option.

From equation (A3), the share of households within income quintile g choosing the outside option is given by:

$$s_{0g} = \frac{\exp(V_{0g})}{\sum_{j=0}^{J} \exp(V_{jg})} \tag{A4}$$

We assume a semi-log functional form for quantity demanded, where quantity measures the number of items. The quantity demanded by a household in income quintile g at store j is given by:

$$q_{jg} = \theta_{0g} + \theta_{1g} \ln(p_j) \tag{A5}$$

In equation (A5), θ_{0g} and θ_{1g} are the parameters to be estimated and do not vary by market. We expect $\theta_{1g} < 0$ to reflect that as prices increase, quantity demanded falls. We use the semi-log functional form to capture diminishing sensitivity: as prices get to higher levels, the rate of decrease in demand slows down.

As equations (A1) and (A5) show, we do not model households as perfect utility maximisers. They select the store to shop at considering only how the price they pay for a fixed basket will affect their utility, but when they come to make purchase decisions they vary how much they buy depending on price, which has additional effects on their utility. We make this simplifying assumption for tractability reasons, but it reflects the plausible situation in which shoppers do not compare the prices of all their intended purchases before choosing where to shop, but rely on overall impressions of price level and rules of thumb.

We aggregate over all households to determine the total quantity demanded across all households shopping at store j:

$$Q_j = \sum_g M_g s_{jg} q_{jg} \tag{A6}$$

where M_g is the number of households in income quintile g.

Each incumbent duopolist d with supermarkets $k \in \mathcal{K}_d$ in a given market has variable profit across all these supermarkets of:

$$\Pi_k = \sum_{k \in \mathcal{K}_d} (p_k - c_k) Q_k \tag{A7}$$

where c_k is the marginal cost of an item. The incumbent chooses prices to maximise variable profits over all stores that it owns in a given market. The first-order conditions for this multi-store joint pricing profit maximisation are derived in Appendix B.

A.2 Entry model

The entry model follows a similar derivation as the base case model, with the following exceptions.

First, the share equations are given by equation (A3), but we also include the entrant's store in the summation in the denominator.

Second, we adjust the share equations in light of a well-known issue with the multinomial logit model that the variance in the error term can be large relative to the deterministic part of the utility function. Since the introduction of a new product results in a draw from the logit distribution, this can result in large utility gains, even if new products are identical to existing products. This can lead to an overstatement of consumer surplus. See Hausman, 1996 (p.230), and specifically Petrin, 2002, who shows that for the introduction of new minivans, the welfare gains from observed characteristics are outweighed by those arising from the logit error term.

A dynamic seen with supermarket entry overseas is that hard discounter entrants to a market often struggle to gain market share.[12] To capture this dynamic, so as to ensure realistic (and conservative) increases to consumer surplus from an entrant despite the potential for overstatement in the multinomial logit model, we make an adjustment to our estimate of household shares. We assume that households have limited attention/information, such that only a fraction, λ_g, of households in income quintile g will consider switching to the new entrant. Goeree, 2008 takes a similar approach, using a logit model to describe choice characteristics for personal computers, with consumers having limited information about product offerings. Abaluck and Adams-Prassl, 2021 analyse a more general discrete choice model, but with application to the logit model, where consumers can be 'asleep' and choose only a default option, rather than making an active choice from all products. In both of these papers, the authors implement

[12] Commerce Commission, 2024b finds that hard discounter entrants in Australia and Finland have had an impact, but it is a 'slow process' to capture market share.

their approach by probability-weighting the consumer share equation (equivalent to equation (A3)) with an equivalent λ_g parameter.

We therefore adjust the share equation in the entry model such that s_{jg} is the weighted-average of the share of households in income quintile g choosing store j in the unweighted entry case and in the base case (where entry has not occurred), with respective weights λ_g and $1-\lambda_g$.

Third, first-order conditions for profit maximisation are not applied to the entrant in the entry model, because the entrant's prices are exogenously determined.

A.3 Parameter derivation

A.3.1 Derivation of α_g

To determine a value for α_g, the sensitivity of utility to basket price, we use the own-price elasticity of s_{jg} with respect to p_j, $\epsilon_{jj,g}$, given by the standard elasticity formula (see also Train, 2009, p.59):

$$\epsilon_{jj,g} = \frac{\partial s_{jg}}{\partial p_j}\frac{p_j}{s_{jg}} \tag{A8}$$

In equation (A8) we calculate $\frac{\partial s_{jg}}{\partial p_j}$ using equations (A3) and (A1). From equation (A3) write the denominator as $X = \sum_{j=0}^{J} \exp(V_{jg})$. Then applying the quotient rule we have:

$$\begin{aligned}\frac{\partial s_{jg}}{\partial p_j} &= \frac{X\frac{\partial}{\partial p_j}\exp(V_{jg}) - \exp(V_{jg})\frac{\partial X}{\partial p_j}}{X^2}\\ &= \frac{-\alpha_g b_g \exp(V_{jg})X + \alpha_g b_g[\exp(V_{jg})]^2}{X^2}\\ &= -\alpha_g b_g\frac{\exp(V_{jg})}{X} + \alpha_g b_g\frac{[\exp(V_{jg})]^2}{X^2}\end{aligned} \tag{A9}$$

By equation (A3), $\frac{\exp(V_{jg})}{X} = s_{jg}$, and therefore we can write equation (A9) as:

$$\begin{aligned}\frac{\partial s_{jg}}{\partial p_j} &= -\alpha_g b_g s_{jg} + \alpha_g b_g s_{jg}^2\\ &= -\alpha_g b_g s_{jg}(1 - s_{jg})\end{aligned} \tag{A10}$$

Substituting equation (A10) into equation (A8) and simplifying yields:

$$\epsilon_{jj,g} = -\alpha_g b_g p_j(1 - s_{jg}) \tag{A11}$$

We use equation (A11) and a value of $\epsilon_{jj,g}$ from the literature to determine a value for α_g using an iterative approach (as described in the main report).

A.3.2 Derivation of β_g

To determine a value for β_g, the sensitivity of utility to assortment, we use the own-price elasticity of s_{jg} with respect to A_j, $\zeta_{jj,g}$, given by:

$$\zeta_{jj,g} = \frac{\partial s_{jg}}{\partial A_j}\frac{A_j}{s_{jg}} \tag{A12}$$

In equation (A12) we calculate $\frac{\partial s_{jg}}{\partial A_j}$ using equations (A3) and (A1). Applying the quotient rule:

$$\frac{\partial s_{jg}}{\partial A_j} = \frac{X \frac{\partial}{\partial A_j} \exp(V_{jg}) - \exp(V_{jg}) \frac{\partial X}{\partial A_j}}{X^2}$$
$$= \frac{\frac{\beta_g}{A_j} \exp(V_{jg}) X - \frac{\beta_g}{A_j} [\exp(V_{jg})]^2}{X^2}$$
$$= \frac{\beta_g}{A_j} \frac{\exp(V_{jg})}{X} - \frac{\beta_g}{A_j} \frac{[\exp(V_{jg})]^2}{X^2} \tag{A13}$$

By equation (A3), $\frac{\exp(V_{jg})}{X} = s_{jg}$, and therefore we can write equation (A13) as:

$$\frac{\partial s_{jg}}{\partial A_j} = \frac{\beta_g}{A_j} s_{jg} - \frac{\beta_g}{A_j} s_{jg}^2$$
$$= \frac{\beta_g}{A_j} s_{jg}(1 - s_{jg}) \tag{A14}$$

Substituting equation (A14) into equation (A12) and simplifying yields:

$$\zeta_{jj,g} = \beta_g(1 - s_{jg}) \tag{A15}$$

We use equation (A15) and a value of $\zeta_{jj,g}$ from the literature to determine a value for β_g using an iterative approach (as described in the main report).

A.3.3 Derivation of θ_{1g}

To derive θ_{1g}, we use the price elasticity of demand for group g, given by:

$$\eta_g = \frac{\partial q_{jg}}{\partial p_j} \frac{p_j}{q_{jg}} \tag{A16}$$

From equation (A5), we calculate this as:

$$\eta_g = \frac{\theta_{1g}}{b_g p_j} \frac{p_j}{q_{jg}}$$
$$= \frac{\theta_{1g}}{b_g q_{jg}} \tag{A17}$$

We can therefore draw values for the price elasticity η_g from the literature, and use these and equation (A17) to derive a value of θ_{1g} using an iterative approach (as described in the main report).

A.3.4 Deriving θ_{0g}

To determine the value of θ_{0g} implied by an estimate of θ_{1g}, we rearrange equation (A5) as:

$$\theta_{0g} = q_{jg} - \theta_{1g} \ln(p_j) \tag{A18}$$

We use this formula to recalculate θ_{0g} for each iteration of our solution, as described in the main report.

Appendix B First-order conditions for multi-store joint pricing

B.1 Profit maximisation

Each incumbent duopolist d with supermarkets $k \in \mathcal{K}_d$ in a given market has variable profit of:

$$\Pi_d = \sum_{k \in \mathcal{K}_d} (p_k - c_k) Q_k \tag{B1}$$

The first-order condition for profit maximisation with respect to the price at store j, p_j, is:

$$\begin{aligned} \frac{d\Pi_d}{dp_j} &= 0 \\ \Rightarrow Q_j + \sum_{k \in \mathcal{K}_d} (p_k - c_k) \frac{\partial Q_k}{\partial p_j} &= 0 \end{aligned} \tag{B2}$$

We decompose this into the own-price and cross-price effects as:

$$\underbrace{Q_j + (p_j - c_j)\frac{\partial Q_j}{\partial p_j}}_{\text{own-price effect}} + \underbrace{\sum_{k \in \mathcal{K}_d k \neq j} (p_k - c_k) \frac{\partial Q_k}{\partial p_j}}_{\text{cross-price effects}} = 0 \tag{B3}$$

We calculate the own-price and cross-price components in the following sections.

B.2 Own-price component of first-order condition

For the own-price component, using equation (A6) and the product rule, we can write $\frac{\partial Q_j}{\partial p_j}$ as:

$$\frac{\partial Q_j}{\partial p_j} = \sum_g M_g \left(\frac{\partial s_{jg}}{\partial p_j} q_{jg} + \frac{\partial q_{jg}}{\partial p_j} s_{jg} \right) \tag{B4}$$

In equation (B4) we note from equation (A10): $\frac{\partial s_{jg}}{\partial p_j} = -\alpha_g b_g p_j (1 - s_{jg})$. We also calculate $\frac{\partial q_{jg}}{\partial p_j}$ using equation (A5) as:

$$\frac{\partial q_{jg}}{\partial p_j} = \frac{\theta_{1g}}{p_j} \tag{B5}$$

Substituting equations (A10) and (B5) into (B4) gives us the following own-price component of the first-order condition with respect to p_j:

$$(p_j - c_j) \sum_g M_g [-\alpha_g b_g s_{jg} (1 - s_{jg}) q_{jg} + s_{jg} \frac{\theta_{1g}}{p_j}] \tag{B6}$$

B.3 Cross-price component of first-order condition

For the cross-price component, using equation (A6) and the product rule, we write $\frac{\partial Q_k}{\partial p_j}$ as:

$$\frac{\partial Q_k}{\partial p_j} = \sum_g M_g \left(\frac{\partial s_{kg}}{\partial p_j} q_{kg} + \frac{\partial q_{kg}}{\partial p_j} s_{kg} \right) \tag{B7}$$

Again, we first calculate $\frac{\partial s_{kg}}{\partial p_j}$, and write the denominator of equation (A3) as $X = \sum_{j=0}^{J} \exp(V_{jg})$. Applying the quotient rule we have:

$$\frac{\partial s_{kg}}{\partial p_j} = \frac{X \frac{\partial}{\partial p_j} \exp(V_{kg}) - \exp(V_{kg}) \frac{\partial X}{\partial p_j}}{X^2} \tag{B8}$$

The first term in the numerator of equation (B8) is equal to 0, since there are no terms in p_j in $\exp(V_{kg})$ (since $k \neq j$). The only terms in p_j are in X (since this is the sum across all stores). So equation (B8) becomes:

$$\begin{aligned}\frac{\partial s_{kg}}{\partial p_j} &= -\frac{\exp(V_{kg})\frac{\partial X}{\partial p_j}}{X^2} \\ &= \frac{\alpha_g b_g \exp(V_{kg}) \exp(V_{jg})}{X^2} \\ &= \alpha_g b_g s_{jg} s_{kg} \end{aligned} \tag{B9}$$

We next note that $\frac{\partial q_{kg}}{\partial p_j} = 0$, since there are no terms in p_j in that equation for $k \neq j$.

Substituting equation (B9) into equation (B7) gives us the following cross-price component of the first-order condition for profit maximisation with respect to p_j:

$$\sum_{k \in \mathcal{K}_d k \neq j} (p_k - c_k) \sum_g M_g(\alpha_g b_g s_{jg} s_{kg} q_{kg}) = 0 \tag{B10}$$

B.4 Full multi-store first-order conditions

Combining equations (B6) and (B10) into equation (B3), the full first-order condition for profit maximisation with respect to p_j across all stores is:

$$Q_j + (p_j - c_j) \sum_g M_g[-\alpha_g b_g s_{jg}(1 - s_{jg}) q_{jg} + s_{jg} \frac{\theta_{1g}}{p_j}] + \sum_{k \in \mathcal{K}_d k \neq j} (p_k - c_k) \sum_g M_g(\alpha_g b_g s_{jg} s_{kg} q_{kg}) = 0 \tag{B11}$$

The form of this equation does not change as between the base case and entry case models, although the inputs will change because the entrant's price is incorporated implicitly (via the share and demand equations).

Appendix C Derivation of consumer surplus

Consumer surplus for a household i in income quintile g is the maximum utility it gains from its choice of supermarket across all stores in the market $j = 0, 1, ..., J$ (which includes the outside option, $j = 0$) expressed in dollars. That is:

$$CS_{ig} = \frac{1}{\alpha_g} \max_j (U_{ijg}) \tag{C1}$$

The division by α_g converts utility measured in utils to utility measured in dollar terms. From equation (A1), the marginal utility for a change in basket price is given by:

$$\frac{\partial U_{ijg}}{\partial (b_g p_j)} = -\alpha_g \tag{C2}$$

As Train, 2009 (pp.56-57) discusses, a one dollar decrease in the price of the basket is equivalent to a one dollar increase in income. Therefore, α_g is the increase in utility for a one dollar increase in income: the marginal utility of income. We assume marginal utility of income does not vary as a result of price changes, which simplifies the analysis (and is a standard assumption in similar models, see e.g., Nevo, 2000).

Following Train, 2009 (p.55), the expected consumer surplus for a multinomial logit model is given by:

$$E[CS_{ig}] = \frac{1}{\alpha_g} E[\max_j (V_{jg} + \xi_{ijg})] \tag{C3}$$

which Train, 2009 shows is equal to:

$$\begin{aligned} E[CS_{ig}] &= \frac{1}{\alpha_g} \ln[\sum_{j=0}^{J} \exp(V_{jg})] \\ &= \frac{1}{\alpha_g} \ln[\exp(V_{0g}) + \sum_{j=1}^{J} \exp(V_{jg})] \end{aligned} \tag{C4}$$

Rearranging equation (A4), we write $\exp(V_{0g})$ as:

$$\exp(V_{0g}) = \frac{s_{0g}}{1 - s_{0g}} \sum_{j=1}^{J} \exp(V_{jg}) \tag{C5}$$

Substituting equation (C5) into equation (C4) gives:

$$E[CS_{ig}] = \frac{1}{\alpha_g} \ln[\frac{\sum_{j=1}^{J} \exp(V_{jg})}{1 - s_{0g}}] \tag{C6}$$

Equation (C6) gives consumer surplus in the base case model. In the entry case model, we calculate consumer surplus both for when all households consider the entrant as an option and when no households consider the entrant as an option and calculate the probability-weighted expected consumer surplus by weighting by λ_g.

We then aggregate over all households, M_g, and across income quintiles g to give:

$$E[CS] = \sum_g \frac{M_g}{\alpha_g} \ln[\frac{\sum_{j=1}^{J} \exp(V_{jg})}{1 - s_{0g}}] \tag{C7}$$

Equation (C7) provides us with our measure of consumer surplus from the factors that affect utility (prices, assortment, and experience) for a given supermarket choice.

However, equation (C7) assumes a fixed basket size despite changes in price between the base case and entry case. We therefore also include a correction to capture changes in welfare driven by a quantity response to changes in price. Individual households may face a change in price between the base and entry cases either because the price at the store where they shop changes or because they change the store where they shop. The change in surplus for an individual household due to a change in the quantity they purchase depends on the parameters of the basket size function and the prices they face in the two cases.

For household i in income quintile g who faces (adjusted) base case price p_i^b and (adjusted) entry case price p_i^e, the change in consumer surplus is given by the traditional triangle area associated with the change in prices, which is:

$$\Delta CS_{ig} = \int_{p_i^e}^{p_i^b} [q_{jg}(p_j) - q_{jg}(p_i^b)] \; dp_j \tag{C8}$$

Substituting equation (A5) for q_{jg} gives:

$$\begin{aligned}
\Delta CS_{ig} &= \int_{p_i^e}^{p_i^b} \theta_{1g}[\ln(p_j) - \ln(p_i^b)] \; dp_j \\
&= \theta_{1g}[(p_j \ln(p_j) - p_j) - (p_j \ln(p_i^b))]\Big|_{p_i^e}^{p_i^b} \\
&= \theta_{1g}[p_i^b \ln(p_i^b) - p_i^b - p_i^b \ln(p_i^b) - p_i^e \ln p_i^e + p_i^e + p_i^e \ln p_i^b] \\
&= \theta_{1g}[p_i^e(\ln(p_i^b) - \ln(p_i^e)) + p_i^e - p_i^b]
\end{aligned} \tag{C9}$$

The independence of irrelevant alternatives (IIA) property of the multinomial logit model means the only households that switch the store where they shop between the base and entry cases are those that shop at an incumbent store in the base case and switch to the new store in the entry case.[13]

We define the proportion of households in each income quintile that shop at the incumbent store j in the base case and remain at j in the entry case as s_{jg}^r and that leave j to switch to the entrant store as s_{jg}^l. The remain group faces (adjusted) prices at store j of p_j^b in the base case and p_j^e in the entry case, while the leave group faces prices of p_j^b and p_{ent}^e in the base case and entry case respectively, where p_{ent}^e is the entrant's price. Substituting the relevant prices into equation (C9) gives the change in consumer surplus for each of the remain group and leave group.

Finally, we sum each of the remain and leave consumer surplus over all households in a market, and add together the totals of the remain and leave groups to give the total correction to the change in consumer surplus.

[13] See, generally, Train, 2009 pp.45-47.