The Impact of Macro Socio-economic Drivers and Fiscal Policy on Expenditure Allocation and Attribute Preferences

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Abstract

Our article investigates the effect of macro socio-economic drivers on Australian households' allocation of expenditure in a category (household appliances) and conditional on the allocated category expenditure, preferences for products (clothes washers) within the category. At the category-level, we quantify the effect of changes in social mobility, disposable income, housing prices and the 2009 stimulus payments on purchase propensity and expenditure. At the product-level, we investigate how households trade off between price, energy efficiency and loading capacity conditional on allocated category expenditure, measuring nonhomotheticity in preferences. We use the model to study a number of hypothetical scenarios, where we simulate the effect of changes in macro socio-economic drivers and fiscal policies on market structure and revenue.

Keywords: Household appliances, clothes washers, nonhomothetic preferences, fiscal stimulus

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> "The radical recasting of federal fiscal policy in response to the global financial crisis in 2008-09 stands out as the *single most important macro-economic policy development this decade* ... Given the tens of billions of dollars of public spending involved, the budget deficit and public debt legacy it has left, as well as the precedent that massive fiscal stimulus has set for responding to future foreign financial crises, evidence-based policy evaluation demands ongoing investigation of its economy-wide impact." - Tony Makin, *The Australian* (italics added)[1]

INTRODUCTION

Successful planning of long-term marketing strategy depends on a comprehensive understanding of consumer reactions to both macro socio-economic drivers and fiscal policy changes (often enacted as a response to a crisis to offset the impact of a negative shock). Without a detailed quantitative assessment of the impact of the macro climate on consumers, a marketing manager will be unable to optimally update strategies (e.g., Gordon et al. 2012 show that price elasticities in a grocery store, and by implication optimal pricing strategies, co-move with gross domestic product). Additionally, studying the impact of policy responses is of import to policy makers tasked with managing the economy. For example, in the recent global crisis, decreased discretionary income, decreased home values (private assets), and decreased social mobility, combined to significantly dampen consumer spending. To encourage consumer spending, governments responded by introducing stimulus measures. For example, the Australian government spent AUS$21 billion on tax bonuses in 2009 (see Leigh 2012 for details). There has been considerable debate on the response of consumers to the fiscal stimulus.

Prior work in both marketing and economics has considered the impact of macro socio-economic drivers on category choice. For example, Du and Kamakura (2008),

[1] http://www.theaustralian.com.au/opinion/fiscal-stimulus-did-not-save-us/story-e6frg6zo-1225897744621

Kamakura and Du (2012) and Dutt and Padmanabhan (2011) study the impact of business cycles, economic contractions/expansions, and currency crises respectively, on category level measures of consumer expenditure. Additionally, Ma et al. (2011) examine the impact of gasoline prices on consumer purchases in the grocery store. Lamey et al. (2007) describes the evolution of private label share across business cycles, while Lamey et al. (2012) investigates the role of marketing conduct in the adoption of private label products across business cycles. Finally, Albuquerque and Bronnenberg (2011) study the impact of an economic crisis on prices and dealer networks in the automobile industry. However, considerably less attention has been paid to the impact of such factors on consumer preferences, and hence rates of substitution across, differentiated products.

Accordingly, our study investigates the impact of changes in income, mobility, and fiscal policy on purchases, and traces the impact of a stimulus payment on category incidence, expenditure and preferences. Substantively, we focus on household appliances (differentiated durable goods), with particular focus on the brand shares of clothes washers. Household appliances represents a large component of the Australian economy, with approximately AUS$6 billion in annual revenue and approximately AUS$600 million in clothes washer sales. A negative change in economic climes affects the demand for household appliances in two ways. First by reducing income, a recessionary shock reduces a consumer's ability to spend in the category. As consumer durables represent significant financial decisions for most households, they are likely to be especially vulnerable to changes in household finances. Second, recessions decrease population mobility (for several reasons including a consumer being locked into a home mortgage). Unique to a small subset of product categories that cater to households changing addresses, the decreased mobility translates into a decrease in the need (and hence decrease in primary demand) for the product.

Methodologically, we build on the *Aggregate Random Coefficients Logit* model henceforth ARCL model (Berry et al. 1995, Sudhir 2001, Chintagunta et al. 2003). First, we specify a dynamic panel model for category consideration (discussed by Ching et al. 2009) and expenditure. Our model controls for both state dependence and unobserved heterogeneity. We use the model to examine the impact of the macro climate on category consideration in addition to the impact on preferences and brand shares. Next, we model the purchase decision for clothes washers. We allow preferences to rotate with the allocated category expenditure, allowing consumer preferences to be nonhomothetic: marginal rates of substitution across alternative products are allowed to change with category expenditure.

We find that nonhomothetic attribute preferences imply that a change in macro socio-economic drivers (which impact households' prosperity) changes aggregate and product level elasticities, brand shares and revenues. For example, we find that households prefer to trade up to larger (and more energy consuming) machines with increasing disposable income, reshaping market structure by changing expenditure allocation and preferences. Further, we simulate the impact of different scenarios that reflect recent events, particularly focusing on the impact of mobility, prices of residential homes and changes in disposable income. Most noteably, our findings suggest that the targeted stimulus used in Australia, with the size of payments aligned with income, had a substantially larger impact than a similar (equivalent in cost to the Australian government) uniform stimulus on total expenditure in household appliances.

More broadly, we answer prior calls to the use of structural models to relate macro socio-economic drivers to consumer behavior (c.f. Hausman 2003, for a discussion on using structural models to develop a more accurate consumer price index). These authors suggest that by treating consumer preferences as primitives, a structural model is better able to understand and predict consumer behavior in different financial climes. Indeed, Dutt and Padmanabhan (2011) suggest that "decision makers seeking to obtain a proper assessment of the impact of [a] crisis on their business need to start by understanding the impact of [the] crisis on their consumer's behaviors." In response to such calls, we simulate and quantify the impact of the macro climate and policy responses on a focal brand or category. Beyond the impact of these on consumer spending, our approach also provides guidance on the ancillary effects of a stimulus on product attributes. Hence, for example, our model can be used to simulate if rebates for cars may increase the likelihood of a consumer trading up to a larger car, with lower gas mileage (and a larger carbon footprint).

The remainder of the paper is structured as follows. In the next section we outline our framework for studying consumer purchases in clothes washers, discuss the major modeling challenges and describe the formal model and our estimation strategy. Next, we describe our findings, both for purchases in consumer appliances and for clothes washers. We conclude by describing our counterfactuals and discussing the substantive implications of our work.

DATA AND MODEL

Data

We estimate the category expenditure model on disaggregate data from the Household Income and Labor Dynamics survey (henceforth HILDA) survey, a longitudinal panel of households that includes a wide range of measurements regarding income, wealth, subjective well-being, family dynamics and expenditures. Wave 1 of the panel started in 2001 with 7,682 households (19,914 individuals), with interviews conducted with all adult members of each household, every year. Across the years, ongoing recruitment efforts are used to counteract panel attrition, and ensure the panel stays representative of the Australian population. The survey includes a measure of the annual spending of each household on household (consumer) appliances, as well as a number of additional household descriptors. Each measure is further cross-validated by HILDA researchers to ensure accuracy.

Second, we model the choice of a product in the category. We build on the ARCL model to allow for nonhomotheticity in preferences. We estimate the product choice model on unit volume data, made available by GfK (Australia and New Zealand) for each state in Australia. The data is based on a retail store audit, collected and commercially sold by GfK to retailers throughout Australia. We use annual data from July 2007 to June 2010. The data includes the average price (transactional price, net of any price promotions) per unit sold, and the attribute level descriptors for all products available for sale in the market.

We focus on two clothes washer attributes: loading capacity and energy efficiency. The loading capacity is the maximum capacity of a clothes washer, measured in kilograms of (dry) clothing. Energy efficiency is measured using the Energy Star rating index. The ”Energy Star” program is a 1992 initiative of the US Environmental Protection Agency. The scale provides consumers with information about the energy efficiency of a product, based on a typical usage profile. In Australia, it is a mandatory requirement for all household appliances to calculate and report their Energy Star rating[2]. The Energy Star rating, ranging from one (least efficient) to five (most efficient), is printed on a prominent label adhered to the machine at point of sale. The program is backed by a range of publicly available information on the correct use, and the basis for computation, of the rating scale.

We focus on the 8 brands with the largest market share in clothes washers (that jointly account for 92.1% of all purchases, with the 9th brand accounting for 1.69% of purchases). While our model does not use any typology of brands (our estimates are agnostic to any classification), to facilitate the discussion of our results, we refer to brands as being lower or higher tier. Our discussions with marketing practitioners in Australia indicate that Bosch is generally regarded as a premium brand, followed closely by Electrolux, Fisher & Paykel and Whirlpool. LG and Samsung are generally perceived as being lower in quality, with Simpson being viewed as an ’entry-level’ brand.

[2]Mandatory eco-labels are also required by other countries. In the USA, for example, manufacturers are required to report estimated annual energy consumption in a ”EnergyGuide” label.

We observe and model shares for each clothes washer stock keeping unit (SKU) sold in Australia. We make two simplifications to reduce outliers where a product was in limited distribution. First, for SKUs that sell less than 50 units in a state and a period (that is for the lowest 1.5% of our sample), we form a composite product for each brand in each state and period, that has the median attribute and median price of the products. Second, we form a composite product for the trade brand, and use the median attributes in the state and period for its attributes.

Formal model

Category expenditure allocation model. A key challenge in modeling cross-category allocations of household expenditure is accounting for households not purchasing in a category (e.g. Du and Kamakura 2008, Drèze et al. 2004). To account for such "corner solutions", we build on the Tobit 2 model (used prior in marketing, e.g. by Algesheimer et al. 2010), and separately model consideration and expenditure. We specify a dynamic panel model, where in state s, year t, for household $h \in \{1, \ldots, H\}$, the decision to purchase ($c_{hst} = \mathbf{1}[c^*_{hst} > 0]$) and expenditure in the category e_{hst} conditional on purchase, is a function of past expenditure (e_{hst-1}), past consideration (c_{hst-1}), observables ($z_{hst} = \{z_{chst}, z_{ehst}\}$) and state and year fixed effects($\{D_{cst}, D_{est}\}$):

$$\text{(1)} \qquad c^*_{hst} = \lambda c_{hst-1} + \theta_c z_{chst} + D_{cst} + \omega_{ch} + \epsilon_{chst},$$

$$\text{(2)} \qquad e_{hst} = \begin{cases} \gamma e_{hst-1} + \theta_e z_{ehst} + +D_{est} + \omega_{eh} + \epsilon_{ehst} & \text{if } c_{hst} = 1, \\ 0 & \text{if } c_{hst} = 0. \end{cases}$$

We treat unobserved household heterogeneity (ω_{ch}, ω_{eh}) and household-period specific *i.i.d.* shocks ($\epsilon_{chst}, \epsilon_{ehst}$) as being zero mean bivariate normal with covariance matrices:

$$\Sigma_\omega = \begin{bmatrix} \sigma^2_{\omega_c} & \rho_{\omega_c,\omega_e}\sigma_{\omega_c}\sigma_{\omega_e} \\ \rho_{\omega_c,\omega_e}\sigma_{\omega_c}\sigma_{\omega_e} & \sigma^2_{\omega_e} \end{bmatrix}, \quad \Sigma_\epsilon = \begin{bmatrix} 1 & \rho_{\epsilon_c,\epsilon_e}\sigma_{\epsilon_e} \\ \rho_{\epsilon_c,\epsilon_e}\sigma_{\epsilon_e} & \sigma^2_{\epsilon_e} \end{bmatrix}.$$

The covariance terms can be combined via summation, with overall covariance structure:

$$\Sigma_{\omega+\epsilon} = \begin{bmatrix} 1+\sigma^2_{\omega_c} & \rho\sqrt{(1+\sigma^2_{\omega_c})(\sigma^2_{\omega_e}+\sigma^2_{\epsilon_e})} \\ \rho\sqrt{(1+\sigma^2_{\omega_c})(\sigma^2_{\omega_e}+\sigma^2_{\epsilon_e})} & \sigma^2_{\omega_e}+\sigma^2_{\epsilon_e} \end{bmatrix}, \tag{3}$$

where the total correlation is:

$$\rho = \frac{\rho_{\epsilon_c,\epsilon_e}\sigma_{\epsilon_e} + \rho_{\omega_c,\omega_e}\sigma_{\omega_c}\sigma_{\omega_e}}{\sqrt{(1+\sigma^2_{\omega_c})(\sigma^2_{\epsilon_e}+\sigma^2_{\omega_e})}}.$$

The expected category expenditure conditional on purchase in the category, for any household h in state s, year t is:

$$E[e_{hst} \mid z_{hst}, c_{hst} = 1] = \Psi_{ehst} + \rho\sqrt{1+\sigma^2_{\omega_c}}\Lambda(a_{hst}), \tag{4}$$

where $a_{hst} = \Psi_{chst}/\sqrt{1+\sigma^2_{\omega_c}}$, $\Psi_{chst} = \lambda c_{hst-1} + \theta_c z_{chst} + D_{cst}$, and $\Psi_{ehst} = \gamma e_{hst-1} + \theta_e z_{ehst} + D_{est}$.

We study the effect of disposable income (net of taxes and governmental transfers), the value of the primary residence (if the household owns the home), and distance moved in the previous year (expressed in kilometers) on category expenditure. Appendix A characterizes properties of the expenditure allocation model. Table 1 reports summary statistics, and provides corresponding HILDA data names.[3]

[Table 1 about here.]

Product choice model. We write the indirect utility for a household h choosing a model of clothes washer j from a choice set J as:

$$V_{hjst} = \alpha_h \log(p_{jst}) + \beta_h \mathbf{x}_j + F_{st} + \xi_{jst} + \zeta_{hjst}. \tag{5}$$

[3] Maintained at http://www.melbourneinstitute.com/hilda/doc/doc_hildamanual.html or available from the Melbourne Institute of Applied Economic and Social Research. Consistent with prior literature, we winsorize, and transform measures to their natural logarithm.

F_{st} is a fixed effect for state and year. The product-specific demand shock, ξ_{jst}, is assumed to be observed by everyone in the market, but unobserved by the researcher. The indirect utility for the outside good is represented by V_{h0st} which represents the option of not purchasing a clothes washer and is assumed to be driven only by total category expenditure and a stochastic term (we normalize $\xi_{0st} = 0$):

$$V_{h0st} = \zeta_{h0st}. \tag{6}$$

The household specific coefficients $\{\alpha_h, \beta_h\} = \{\alpha_h, \beta_{h1}, \ldots, \beta_{hR}\}$ are modeled as comprising of three terms: (a) a homogenous component, common across all households, (b) a heterogenous component that is distributed multivariate normal across households, and (c) a component that is directly proportional to the expected category expenditure, conditional on category consideration. For notational convenience, denote a vector $\nu_h = \{\nu_{h\alpha}, \nu_{h1}, \ldots, \nu_{hR}\}$ as a draw from a multivariate *iid* standard normal distribution ($N(0, \mathbf{I})$, denoted by F_ν). Then each coefficient, is the sum of the mean coefficient (common across households), ν_h multiplied by the corresponding standard deviation for the coefficient (e.g. κ_α for price), and a coefficient, (e.g. κ_{ep}) multiplied by the expected category expenditure allocation e_{hst}. Separating the indirect utility into mean utility, and deviations from the mean, based on (5) and (6), implies:

$$V_{hjst} = \delta_{jst}(\mathbf{x}_j, p_{jst}; \alpha, \beta, F_{st}, \xi_{jst}) + \mu_{hjst}(\mathbf{x}_j, p_{jst}, e_{hst}; K) + \zeta_{hjst}, \tag{7}$$

where the homogenous component is $\delta_{jst} = \alpha \log(p_{jst}) + \beta \mathbf{x}_j + F_{st} + \xi_{jst}$, and the heterogenous component is:

$$\mu_{hjst}(\mathbf{x}_j, p_{jst}, e_{hst}; K) = \left(\kappa_\alpha \nu_{h\alpha} + \kappa_{ep} e_{hst}\right) \log(p_{jst}) + \sum_{r=1}^{R} \left(\kappa_r \nu_{hr} + \kappa_{er} e_{hst}\right) x_{rj}. \tag{8}$$

$K = \{\kappa_\alpha, \kappa_{ep}, \kappa_1, \kappa_{e1}, \ldots, \kappa_R, \kappa_{eR}\}$ is the set of heterogeneity and nonhomotheticity parameters on price and observed characteristics.

We provide a framework for measuring nonhomotheticity. As we study durable differentiated goods, consistent with Fader and Hardie (1996) and Bell et al. (2005), we treat choices as customers' evaluations across sets of attributes and model attribute-level preferences. "Engel curves", named after Ernst Engel, describe changes in expenditure on a product or category with changes in economic resources (for example, household income). Hence, we label parameters that govern changes in utility with e_{hst}, as "Engel parameters" (κ_{ep} and $\kappa_{er}, r = 1, \ldots, R$). A formal test for homotheticity is the hypothesis that $\kappa_{er} = \kappa_{eR} = \kappa_{ep} = 0$, $\forall r = 1, \ldots, R$. Our article thus provides evidence on consumers rotating towards or rotating away from clothes washer attributes with changes in expenditure allocation. Note that while our model is related to Allenby and Rossi (1991), our model is less restrictive as it allows customers to rotate toward or away, from different attributes. Integrating over ζ_{hjst} (assuming ζ_{hjst} is *i.i.d*. extreme value), the probability of household h purchasing product j, when faced with the allocation e_{hst} for the category is:

$$P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, c_{hst} = 1; \alpha, \beta, F_{st}, \xi_{jst}, K) =$$

$$\frac{\exp\left\{\delta_{jst}(\mathbf{x}_j, p_{jst}; \alpha, \beta, F_{st}, \xi_{jst}) + \mu_{hjst}(\mathbf{x}_j, p_{jst}, e_{hst}; K)\right\}}{1 + \sum_{k=1}^{J} \exp\left\{\delta_{kst}(\mathbf{x}_k, p_{kst}; \alpha, \beta, F_{st}, \xi_{kst}) + \mu_{hkst}(\mathbf{x}_{jst}, p_{jst}, e_{hst}; K)\right\}}. \tag{9}$$

To reduce notational clutter, we abuse notation by dropping the parameters from the expression, and write

$P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, c_{hst} = 1) = P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, c_{hst} = 1; \alpha, \beta, F_{st}, \xi_{jst}, K)$.

Integrating over households, the market share of product j in state s and time t, s_{jst} is:

$$s_{jst} = \int_{\mathbb{H}} \int_{\mathbb{R}^{1+R}} \underbrace{P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, c_{hst} = 1)}_{\text{I}} \underbrace{P(d\nu_{hst})}_{\text{II}} \underbrace{P(c_{hst} = 1 \mid h_{hst})}_{\text{III}} \underbrace{P(h_{hst})}_{\text{IV}}, \tag{10}$$

The first component (I) is the probability of purchasing product j conditional on the attributes and prices of the products available in the choice set, heterogeneous preferences, allocated category expenditure and the household considering the category. The second component (II), describes unobserved cross-household heterogeneity in the $1 + R$ heterogenous attributes. The third component (III) is the conditional category consideration probability, given household h with characteristics h_{hst}. The fourth component (component IV) is the probability that a household with characteristics h_{hst} exists in the population ($\mathbb{H}$), as estimated by HILDA. Thus, we model market share as being the expected probability of purchasing product j conditional on the attributes and prices of the products available in the choice set, with expectations taken over the $1 + R$ nuisance parameters and HILDA estimated probabilities.

Model analytics

We derive four metrics that capture the impact of a change in a socio-economic driver, on household purchases. The first three metrics[4] correspond to measuring changes in the probability of purchasing a household appliance, the expected expenditure in household appliances, conditional on purchase, and the change in clothes washer purchase probability, with a change in a socio-economic driver. The fourth metric characterizes the change in price elasticity, thus accounting for the tertiary impact of a change in the macro climate on market structure (by changing preferences and hence elasticity). While we can derive an analogous metric for any marketing mix instrument, we choose to focus on price as it is the most salient marketing instrument in our context. Additionally, Gordon et al. (2012) focus on measuring changes in price elasticity in differentiated consumer packaged goods with the macro climate. As we focus on measuring similar constructs in differentiated durables, our studies are complementary in developing empirical generalizations. When considering either the probability of a household

[4]To ease exposition, we discuss household elasticities. To obtain corresponding aggregate demand elasticities, the analyst can marginalize household-level derivatives (e.g. $\frac{\partial P(c_{hst}=1|z_{hst})}{\partial z_{rhst}}$), over households to obtain rates of changes in aggregate variables.

purchasing a household appliance, or a clothes washer, we use quasi elasticities[5] in place of elasticities. The household consideration quasi elasticity is (see Appendix B):

$$\eta_{P(c_{hst}=1|z_{hst}),z_{rhst}} = \frac{|\theta_{cr}|\phi\left(a_{hst}\right)}{\sqrt{1+\sigma_{\omega_c^2}}\Phi\left(a_{hst}\right)} = \frac{|\theta_{cr}|\Lambda\left(a_{hst}\right)}{\sqrt{1+\sigma_{\omega_c^2}}},$$

where $\Lambda = \phi/\Phi$ is the inverse Mills ratio, and $a_{hst} = \Psi_{chst}/\sqrt{1+\sigma_{\omega_c^2}}$. Assuming that e_{hst} is expressed in logarithmic scale, the category expenditure elasticity, conditional on category consideration, is (see Appendix B for a derivation):

$$\eta_{E[e_{hst}|z_{hst},c_{hst}=1],z_{rhst}} = |\theta_{er} - \rho\theta_{cr}\Lambda(a_{hst})(a_{hst} + \Lambda(a_{hst}))|. \tag{11}$$

If $\frac{\partial P(c_{hst}=1|z_{hst})}{\partial z_{rhst}} > 0$ and $\frac{\partial E[e_{hst}|z_{hst},c_{hst}=1]}{\partial z_{rhst}} > 0$, as in our application,[6] then the quasi elasticity of purchasing product j with respect to z_{rhst} is (see Appendix B):

$$\begin{aligned}\eta_{P(j|\mathbf{x}_{st},\mathbf{p}_{st},\nu_{hst},z_{hst}),z_{rhst}} = \Big|&\eta_{P(c_{hst}=1|z_{hst}),z_{rhst}} + \\ &\eta_{E[e_{hst}|z_{hst},c_{hst}=1],z_{rhst}}\left(\sum_{r=1}^{R}\kappa_{er}\Delta x_{jrst} + \kappa_{ep}\Delta p_{jst}\right)\Big|,\end{aligned} \tag{12}$$

where

$$\Delta x_{jrst} = \left(x_{jrst} - \sum_{k=1}^{J} P(k \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, e_{hst}, c_{hst}=1)x_{krst}\right),$$

and

$$\Delta p_{jst} = \left(p_{jst} - \sum_{k=1}^{J} P(k \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, e_{hst}, c_{hst}=1)p_{kst}\right).$$

are mean-centered deviations (arithmetic mean, weighted by the conditional probability of purchase of each product) of the focal product's attribute r, and price, respectively.

If the Engel parameters are zero, macro climate changes cause category expansion or

[5] Quasi elasticities describe changes in the conditional probability of an event, with respect to a change in a focal variable. The quasi elasticity of e w.r.t. x, expressed in logarithmic form, is $\eta_{e,x} = |\frac{\partial log(P(e|x))}{\partial x}|$.

[6] It is straightforward to extend our results to alternative cases. For brevity, we focus on the case that corresponds to our application.

contraction but do not affect product shares. If the Engel parameters are non-zero, then the sum of the deviations for each brand (across attributes) influences the degree of rotation towards or away from the brand. For example, with increasing disposable income, if a household increases the allocated expenditure for the category, then its demand for product j will depend on the match between the attributes of product j, and the household's increasing/decreasing sensitivity to those attributes. If the product is inferior, in the sense of possessing attributes that the household rotates away from with increased expenditure allocations, then its demand elasticity for product j may be negative. Conversely, products benefit from negative macro socio-economic changes if the Engel rotation is sufficiently large to induce an increase in shares and revenue that offsets category contraction. Specifically in a category where disposable income has a non-negative impact on category consideration and category expenditure allocation ($\frac{\partial P(c_{hst}=1|z_{hst})}{\partial z_{rhst}} > 0$ and $\frac{\partial E[e_{hst}|z_{hst},c_{hst}=1]}{\partial z_{rhst}} > 0$) products benefit from a negative shock if:

$$\left(\sum_{r=1}^{R} \kappa_{er}\Delta x_{jrst} + \kappa_{ep}\Delta p_{jst}\right) < -\frac{\eta_{P(c_{hst}=1|z_{hst}),z_{rhst}}}{\eta_{E[e_{hst}|z_{hst},c_{hst}=1],z_{rhst}}}. \tag{13}$$

The Engel parameters also lead to a change in the quasi price elasticity with macro socio-economic drivers, with the rate of change being a function of the propensity, expenditure allocation and Engel parameters. For different parameter values, the quasi price sensitivity in a category may be increasing, unaffected, or decreasing relative to disposable income. Specifically, the rate of change of the quasi price elasticity with respect to z_{rhst} for household h in state s, time t, assuming $\frac{\partial E[e_{hst}|z_{hst},c_{hst}=1]}{\partial z_{rhst}} > 0$, is (see Appendix C for a derivation):

$$\begin{aligned}\frac{\partial \eta_{P(j|\mathbf{x}_{st},\mathbf{p}_{st},\nu_{hst},z_{hst}),p_{jst}}}{\partial z_{rhst}} \quad = \quad & \left(1 - Pr_{jhst|c_{hst}}\right) sgn\left(\alpha + \kappa_\alpha \nu_{h\alpha} + \kappa_{ep} e_{hst}\right) \kappa_{ep}\eta_E \\ & - Pr_{jhst|c_{hst}} \left(\sum_{r=1}^{R} \kappa_{er}\Delta x_{jrst} + \kappa_{ep}\Delta p_{jst}\right) \eta_E |\alpha + \kappa_\alpha \nu_{h\alpha} + \kappa_{ep} e_{hst}|,\end{aligned} \tag{14}$$

where for brevity, we define $Pr_{jhst|c_{hst}} = P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst} = 1)$, $sgn\,(x)$ is a step function indicating the sign of x, and $\eta_E = \eta_{E[e_{hst}|z_{hst}, c_{hst}=1], z_{rhst}}$. There are two special cases where Equation (14) implies that quasi price sensitivity is not affected by macro climate changes. First, if a macro socio-economic driver does not affect category expenditure allocation ($\eta_E = 0$), and second if the Engel rotation parameters are zero (consumer preferences are homothetic).

Estimation strategy

In the category expenditure allocation model we estimate $\Theta = \{\theta_c, \theta_e\}$ (the effect of covariates on the propensity and expenditure), λ (category-level state dependence in propensity), γ (category-level state dependence in expenditure), and the covariance parameters Σ_ω and Σ_ϵ. The likelihood of household h's category-level decisions is:

$$\begin{aligned}
L_h(\Theta, \lambda, \gamma, \Sigma_\epsilon \mid \omega_h) &= \prod_{t=1}^{T} L_{hst}(c_{hst}, e_{hst} \mid \omega_h), \\
&= \prod_{t=1}^{T} \left(P[c^*_{hst} < 0]^{(1-c_{hst})} \left(f(e_{hst} \mid c^*_{hst} > 0) P[c^*_{hst} > 0] \right) \right)^{c_{hst}}, \\
&= \prod_{t=1}^{T} \Phi\left[-\left(\Psi_{chst} + \omega_{ch} \right) \right]^{1-c_{hst}} \left[\frac{1}{\sigma_{\epsilon_e}} \phi \left(\frac{e_{hst} - (\Psi_{ehst} + \omega_{eh})}{\sigma_{\epsilon_e}} \right) \right. \\
&\qquad \left. \Phi \left(\frac{\Psi_{chst} + \omega_{ch} + \frac{\rho_{\epsilon_c, \epsilon_e}}{\sigma_{\epsilon_e}} (e_{hst} - (\Psi_{ehst} + \omega_{eh}))}{\sqrt{1 - \rho^2_{\epsilon_c, \epsilon_e}}} \right) \right]^{c_{hst}}.
\end{aligned} \tag{15}$$

We marginalize over H households' unobserved components to derive the joint likelihood (across multiple time periods), and estimate by the method of maximum likelihood;

$$L(\Theta, \lambda, \gamma, \Sigma_\omega, \Sigma_\epsilon) = \int_{\mathbb{R}^2} \prod_{h=1}^{H} L_h(\Theta, \lambda, \gamma, \Sigma_\epsilon \mid \omega_h) f(\omega_h) d\omega_h. \tag{16}$$

We use bivariate Gauss-Hermite quadrature to marginalize over unobserved heterogeneity (see Raymond et al. 2010 for details), and BOBYQA (see Powell 2009) to find the argmax. As the HILDA data is longitudinal, identification proceeds from changes in household level socio-economic descriptors, and in the expenditure allocated to the category for each household. Heuristically, identification of heterogeneity stems from similarities in household decision patterns across periods, while identification of the idiosyncratic component of the unobserved shocks stems from changes in decision patterns, across periods.

We estimate the model of clothes washer choice, using the generalized method of moments. We invert shares to recover $\xi_{jt}(K)$. We construct and minimize the objective function, $\hat{m}(K)' W \hat{m}(K)$, where Z_{jt} is the instrument vector, $\hat{m}(K)$ is the sample analog of population moments $Em(K) = EZ'_{jt}\xi_{jt}(K)$, and W is a weight matrix. We estimate the model under the assumption of homoskedastic errors. Next, we use the estimated demand shocks (at the argmin) to update the weight matrix and re-estimate the model. We use 500 Sobel draws (to ensure quadrature accuracy) when integrating over the heterogeneous component of the utility function. Identification in the product choice model is driven by changes in the distribution of the latent category expenditure and purchase probability, across households, across years.

We treat prices as being endogenous. Following Nevo (2001) we use the following instruments: the sum of attributes of competing brands, by brand, and the price of the same clothes washer in other states. When the price of the clothes washer in other regions is not available, we use the average price of clothes washers in the region. This approach is consistent with prior applications of the ARCL model and is well supported in our substantive application as we (a) choose a mature product category with limited technological change in the period of interest, and (b) study demand in a country that represents a small portion of worldwide household appliances. Additionally, (c) as clothes washers are either imported into Australia or have several imported components, exchange rate fluctuations induce correlations in prices across regions, independent of unobserved demand shocks.

Table 2 describes the the average loading capacity, energy efficiency, and the number of unique SKUs of clothes washers, by state and year. In addition, table 2 includes a description of clothes washer sales. Over the years, there is no clear pattern of a change in clothes washer SKUs, as expected in a mature product category. We see that sales of clothes washers increased across Australia from 2007 to 2008, by 4.4 per cent on average (with differences across states). In contrast, in 2009, sales decreased by approximately 7.5% across states. Table 3 describes attribute and brand shares (aggregated across states). We see that a few of the brands (e.g. Samsung, LG) increased shares, while others (e.g. Bosch) decreased in shares. Shares of high capacity clothes washers increased by 4%, while high energy efficiency washer shares decreased by 9%, amounting to approximately a 120,000 unit decline in demand.

[Table 2 about here.]

[Table 3 about here.]

Household expenditure allocation

Table 4 reports results for both the homogenous (estimated setting heterogeneous parameters to be 0) and heterogenous category expenditure models, including estimates of the distribution of household level unobserved heterogeneity in expenditure allocation, ω. We find that including the heterogenous component reduces the magnitude of the variance of the consideration and expenditure equations (σ_ϵ), and attenuates the correlation among the two equations ($\rho_{\epsilon_c,\epsilon_e}$). The high negative correlation among the consideration and expenditure equations can be interpreted to mean that smaller expenditures tend to be made more frequently. The high negative correlation among heterogeneity terms combined with a small positive correlation among the stochastic terms of the consideration and expenditure equations, balance out to give a small negative (not statistically significantly different from zero) total correlation across the two equations (ρ) of -0.012 (standard error = 0.023, computed by the delta method).[7]

[Table 4 about here.]

We find that the heterogenous model is well supported by the data, with the goodness of fit statistic based on the likelihood ratio ($\Delta G^2 = -2 \log LL_{\text{homogenous}} + 2 \log LL_{\text{heterogenous}}$ = 719, with $p = \text{Prob}(\chi^2_3 \geq \Delta G^2) < 0.001$). Hence, we report results based on the heterogeneous specification. We find all three drivers are positive and significant, suggesting that they are positively associated with both higher likelihood of purchasing household appliances, and higher expenditure allocation conditional on purchase. Of these, disposable income is the largest driver in both equations. Past consideration in the category has a moderate positive effect on current consideration, suggesting a degree of persistence in category consideration. While we do not report fixed effects for state and years, we find a statistically significant negative effect in 2009 for category consideration (with 2007 as the base year).

Results for choice among clothes washers

Table 5 reports estimates from the ARCL model including the Engel rotation parameters. The top panel presents the linear components of the model (relating to the attributes of energy efficiency and loading capacity, and price), and the bottom presents the "non-linear" parameters, which are driven by heterogeneity and the Engel rotation. We omit estimates of the dummies (brand, year and state fixed effects) for brevity. Except for the intercept, all reported linear estimates are statistically significant. All Engel parameters, except energy efficiency, are statistically significant. The heterogeneity parameters for price and loading capacity, suggest that there is considerable variation

[7] $cov(\hat{\rho}) = D_\Theta \hat{\Sigma}_\Theta D'_\Theta$ where $\Theta = [\rho_\epsilon, \rho_\omega, \sigma_{\epsilon_e}, \sigma_{\omega_c}, \sigma_{\omega_e}]$ is the vector of estimated parameters, $\hat{\Sigma}_\Theta$ is the covariance of estimates and D_Θ is a vector of the partial derivatives of ρ, with respect to elements in Θ.

across households in price sensitivity and preference for the loading capacity of clothes washers. The Engel parameter for price is negative, suggesting that households with greater expenditure allocations are more price sensitive. The baseline (intercept) Engel parameter is negative, while the Engel parameter for loading capacity is positive, which taken together suggests a rotation in preference towards larger loading capacity machines, with increased category expenditure allocation. Finally, in support of the validity of the instruments, the J-test for overidentifying restrictions, admits the null ($p = \text{Prob}(\chi^2_{11} \geq 0.010) < 0.001$).

[Table 5 about here.]

Elasticities

Table 6 presents summary statistics for the category consideration elasticity (Equation 11), category expenditure allocation elasticity (Equation 12), and product demand elasticity. We find that disposable income has the largest impact on each of these elasticity metrics, followed by mobility, then residential home prices. While Table 6 averages elasticities across products and households, Figure 1 is a histogram describing average clothes washer quasi elasticities with respect to disposable income, by product. There is considerable heterogeneity in the elasticities across products, which we attribute to the amount of product differentiation and nonhomotheticity. These differences (across products) in elasticity have an important implication: brands, through their product portfolios, will likely be affected differently by changes in disposable income.

[Figure 1 about here.]

[Table 6 about here.]

COUNTERFACTUALS: DEMAND IMPACT OF MACRO SOCIO-ECONOMIC SHOCKS

Scenarios

We choose scenarios analogous to those discussed in the extant literature. Given the impact of each scenario on the distribution of household socio-economic conditions, we predict changes in aggregate purchase patterns by aggregating over household purchase decisions. Our paper thus provides conservative guidance on the impact of such macro climate on revenues of focal products or brands (the variables of interest to a marketing manager).

We focus on changes in the three socio-economic variables considered in the model: mobility (distance moved by households in the year), residential property prices and a change in disposable income. To examine the impact of an increase in social mobility, in scenario 1, we simulate the effect of 10% of households that did not relocate in 2009, moving by distances drawn from the empirical distribution. In scenario 2, we examine the impact of a decrease in property prices (and hence the value of residential homes) by 10%. And in scenario 3, we examine the effect of a 10% decrease in disposable income for all households.

We consider three fiscal policy scenarios, that provide more detailed insights about the impact of redistributions of incomes. In scenario 4 (”Robin Hood” policy), we consider the impact of reducing the disposable income of the top decile of earners in Australia by 10%, and redistributing their wealth uniformly across all other households. Broadly, this simulates the impact of wage redistribution by increasing/decreasing marginal tax rates, and governmental transfers, to change the income distribution (reduce income inequality). Figure 2 describes the distribution of received benefits of the observed stimulus in 2009 when the total stimulus payment per household depended on the composition of the household. Scenario 5 simulates shares in the absence of observed stimulus payment. Scenario 6 examines an alternative cost-neutral uniform stimulus where the total stimulus is distributed uniformly across households in Australia.

[Figure 2 about here.]

Impact on total demand for household appliances and clothes washers

The relative impact on clothes washers compared to the impact on consideration and expenditure household appliances, differs markedly across scenarios. Table 7 describes changes in the number of households purchasing household appliances (rows labeled ”HN”), total expenditure in household appliances (rows labeled ”HE”) and on clothes washers (rows labeled ”CW”) in each scenario. Scenarios 1 and 2 lead to small changes in all metrics. We find that scenario 3, a 10% decrease in disposable income, has the largest effect on aggregate demand for clothes washers. In this scenario, the expected impact is approximately 2% on household appliance expenditure, and 0.56% on clothes washer sales. The ”Robin Hood” policy (scenario 4), predicts a moderate increase in consideration and expenditure on household appliances, but a small decrease in clothes washer sales.

In scenario 5, we find that the stimulus payments increased purchase incidence in household appliances, with an additional 50,923 households purchasing household appliances, and a total increase in category expenditure of AUS$60.415 million. Note that scenario 5 simulates the impact of the absence of observed stimulus payments. Hence, results relevant to this scenario should be interpreted in reverse if considering the impact of the stimulus payments. The impact of the stimulus on clothes washers was more limited, with a net increase of 197 units, and a total revenue increase of AUS$133,000. In contrast, the alternative uniform stimulus (scenario 6), relative to the targeted stimulus *increases* category incidence for household appliances with an additional 1,731 households buying within the category, but *decreases* total category expenditure by approximately AUS$1.599 million, relative to the targeted stimulus. Compared with the uniform stimulus, the targeted stimulus also leads to lower sales in clothes washers (698 fewer units and AUS$549,000 less in total expenditure). That is the uniform stimulus is more effective than the targeted stimulus in increasing household appliance purchase incidence, but not as effective in increasing expenditure on household appliances.

[Table 7 about here.]

Impact on clothes washer sales: product differentiation

Across scenarios, in contrast to the relatively small changes in aggregate clothes washer demand, our results suggest the presence of relatively large changes in demand for different clothes washer SKUs. These large changes in share and revenue, which differ in both the direction and magnitude across SKUs, are consistent with our findings of large product elasticities (as described in Figure 1). We find that, although the primary demand effect tends to be fairly consistent across washers, substitution effects cause different products to benefit/lose on net from changes in the macro climate, implying that the demand elasticities are primarily driven by substitution across washers, rather than by category expansion/contraction.

To understand the role of product differentiation, we divide clothes washers into four groups, based on loading capacity (high: ≥ 7 kg, and low capacity: ≤ 6 kg) and energy efficiency (high :≥ 4 stars versus low energy efficiency: ≤ 3 stars). The four "box and whisker" plots in Figure 3(a) describe percentage share changes within each group of products, with each panel representing a group of products.[8] Across the four groups, the "low kg, low energy efficiency" machine is seen to be most vulnerable to macro socio-economic drivers.

[Figure 3 about here.]

We use weighted least squares to analyze which models benefited more/less from the stimulus payments. We regress the average percentage change in shares on loading

[8]The "box" describes the interquartile range, the dots represent observations outside the interquartile range. The "whiskers" are vertical lines connecting the 95th percentile interval. The horizontal line inside each box is the median.

capacity, energy efficiency and brand fixed effects (specified as contrasts relative to the private label). We include the interaction of loading capacity and energy efficiency to control for size-specific effects of energy efficiency. We find that the share changes are predicted by product attributes (see Table 8). We find that loading capacity is a determinant of share changes in all but the sixth scenario. Energy efficiency predicts share changes in the fourth and fifth scenario.

The regression provides us with a tool for predicting changes in share due to the stimulus payments. For example, the regression suggests that on average the market share of a 9 kg machine with 1 star energy efficiency, increased by 5% due to the stimulus. We find that the stimulus payments (in 2009) likely led to a decrease in sales of smaller (less energy consuming[9]) clothes washers in favor of larger (more energy consuming) clothes washers; Table 8 shows that shares of large clothes washers increased due to the stimulus.

[Table 8 about here.]

Impact on clothes washer sales: brands

As brought out in the analytical results, a brand is vulnerable to changes in the macro climate based on its assortment. For example, if a brand's product assortment consists of large clothes washers then our previous results suggest the brand would fare poorly in recessions (with decreases in disposable income). The box and whisker plots (Figure 3b) describe changes in shares for products sold by the eight largest brands. The height of the box and whisker plots demonstrates that for several brands, their SKUs are susceptible to large (positive and negative) changes in demand. However, the median line being close to zero for a number of brands suggest that that these brands are well diversified to dampen the effect of the macro climate. We find that scenarios 1, 2 and 4

[9] Larger washing machines, holding energy efficiency constant, tend to be more energy consuming, predominantly due to the need to heat a larger volume of water.

have a relatively smaller impact on brand shares, while scenarios 3 and 5 have relatively larger effects. In scenario 6 (the uniformly allocated stimulus) brand shares are similar to those seen in the observed stimulus (base line scenario).

In Table 9, we separate between the primary demand effect (the increase/decrease in the number of units sold due to category expansion/contraction, labeled ”PD (#)”), and the substitution effect (the increase/decrease in units sold due to consumers substituting to/from focal products, labeled ”MS (#)”), in each scenario, by brand (see van Heerde et al. 2003, for a detailed exposition). The effects of the substitution, even at the brand level, tend to be the dominant component of demand changes across scenarios. Across the scenarios we see a number of situations where the market share effect moves opposite to the primary demand effect. In Table 10, we tabulate the effect on demand for products of different brands (we drop ”Bosch” and ”LG” to simplify analysis) of the stimulus (scenario 5).

[Table 9 about here.]

[Table 10 about here.]

Often policy makers are more interested in the success/failure of policy to increase the revenue of a domestic/regional brand than an imported brand. For example, in the last recession, U.S. policy makers were more interested in ensuring that the ”Detroit Three” automobile makers benefited from policy interventions to ensure the survival of the American automobile industry, than in promoting sales of competing imported brands. In our context, two regional brands of appliances, Fisher & Paykel and Simpson, are of specific interest to local policymakers as their success/failures have broader economic consequences for Australia and New Zealand. In Tables 9 and 10 we see that both brands were *negatively* affected by the stimulus payments. Our results suggest that the stimulus payments led to consumers substituting towards larger washers. As both brands on average sell smaller clothes washers, they consequently saw a decrease in sales, while competing brands that sell larger washers (e.g. Electrolux and Whirlpool) saw an increase in sales. Conversely, we find that the brands benefit from decreasing incomes (scenario 3) as that leads consumers to substitute towards smaller washers, and hence their product assortments.

CONCLUSION

Traditionally, macroeconomists have been more interested in modeling changes in expenditure (for example, total spending on durables) due to changes in the macro climate, without delving into questions relating to market structure and product shares. Some recent work has explored the role of demographics (such as income, population, family structure and age) on preferences and choice (see Heathcote et al. 2009 for a review). However, thus far, the extant literature has neglected nonhomotheticity (as pointed out by Krusell and Smith 2006): that is, does a household that changes its expenditure in a category, also change its purchase patterns within the category?

Our article develops and applies a framework for identifying and simulating the impact of such macro socio-economic drivers on purchase patterns, and preferences at the category, brand and product level, and focuses on a specific category and sub-category to illustrate the use of the model. There are several other industries to which the framework could be applied. For example, the automobile industry is impacted by the interest rate, which often dictates the purchasing power of the consumer. Understanding the impact of such drivers is important for both managers, who must continually update their marketing mix, and for policy makers, who formulate appropriate responses. Indeed, coupled with a model that predicts changes in macro socio-economic drivers, the insights generated may lead to an avenue for growth for firms able to plan and optimize for changes in consumer preferences.

Our analytical results reveal, inter alia, that the effect of macro socio-economic drivers depends on the Engel parameters and the extent to which products and brands are differentiated. In our application, we find that while individual products and brands (in clothes washers) are affected differently by changes in macro socio-economic drivers, when considering aggregate category revenue these effects often cancel out. That is, the high degree of product substitution explains why we observe comparatively smaller changes in the impact of such drivers at the category-level, than at the product-level.

An important message of our paper is that products differ in their vulnerability to the macro climate, with the net impact on a brand hinging on its product line. It is crucial for brands to assess their exposure to changes in macro socio-economic drivers. Our model provides a tool to translate changes in the distribution of household specific variables, into their impact on expenditure and choices for a focal set of products. Thus, our model can be used by brand managers to compare the performance of candidate product portfolios under different macro conditions. Our approach also enables policy makers to quantify the market level impact of policies that change distributions of, for example incomes, as showcased by scenarios 4, 5 and 6. Our findings suggest that there may be ancillary effects from such policies on the size of clothes washers preferred, and thereby aggregate energy consumption. Such findings resonate with a growing interest in the impact of policy on consumer behavior. For example, Knittel (2011) finds that low gasoline prices (favored by U.S. policymakers) have resulted in American consumers purchasing larger, more powerful and hence more energy consuming cars.

Methodologically, we contribute to the literature by combining a disaggregate dataset describing household level financial variables, and aggregate data describing market shares. This data structure is fairly commonly encountered in marketing, where individual or household data describes purchases or consumer behavior without measuring brand choices, and (aggregate) market share data describes consumer purchases, aggregated across a market. For example, while some datasets study individual consumer decisions (for example, patient compliance), other datasets describe aggregate purchases (market shares of competing brands). In such cases, our framework may allow for more granular inference (for example, measuring the impact of a policy intervention to increase patient compliance, on a focal product's share and revenue).

While we view this study as a useful step in exploring the implications of macro socio-economic drivers on consumers, our study has limitations that offer opportunities for further research. We abstract from modeling forward-looking behavior. Anecdotal evidence strongly suggests that households typically do not wait for lower prices or improved technology when purchasing clothes washers. Further, in order to enrich the model and allow for forward-looking consumers, we would need to observe (or impute) the stock of consumer durable, in each household, in each period. To the best of our knowledge, there is no comparable dataset that records the stock of durable goods, across Australia, for different states and years.

In the spirit of comparative statics, scenarios examined in our paper look at the (partial) impact of a change in only one variable per scenario (to ease inference and analysis). Our simulations can easily be extended to account for changes in multiple variables, and measured over a number of years. As the impact of changes in multiple macro drivers likely compound, in practice, analysts would benefit from building on our simulations and consider the *combined* impact of multiple drivers.

Finally, future studies may explore the impact of macro climate on competition. Some evidence on changes in marketing conduct has been offered by Lamey et al. (2012) for 106 consumer packaged goods categories. In general, studying marketing conduct co-movement requires substantially longer panel datasets than we have access to. In addition, in durable products, technological change and firm entry/exit likely compound data requirements. However, our findings taken together with the extant literature imply that elasticities likely evolve over time due to changes in consumer preferences and it would be of interest to trace the impact of such changes in demand primitives on marketing conduct and competition.

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Year	Description	NSW/ ACT	QLD	SA/NT	VIC/TAS	WA
2007	Disposable Income	44,418	44,788	36,509	44,043	45,544
	Mobility	8.60	10.54	4.63	4.5	5.99
	Value of Primary Residence	399,870	370,732	262,944	344,623	521,329
	Expenditure on Household Appliances	677	629	605	707	915
2008	Disposable Income	44,784	45,921	35,915	47,022	46,318
	Mobility	5.59	9.75	11.26	7.03	12.47
	Value of Primary Residence	402,944	380,629	266,970	374,315	494,607
	Expenditure on Household Appliances	604	669	576	681	839
2009	Disposable Income	47,259	49,278	39,789	47,386	52,421
	Mobility	7.32	8.05	6.46	4.99	7.73
	Value of Primary Residence	405,218	372,508	280,357	381,701	506,376
	Expenditure on Household Appliances	614	669	521	766	787

Table 1: Mean Household Demographic Descriptor, by State and Year.

State Acronyms:

NSW/ACT: New South Wales/Australian Capital Territory;
QLD: Queensland;
SA/NT: South Australia/Northern Territory;
VIC/TAS: Victoria/Tasmania;
WA: Western Australia.

Source: HILDA. Corresponding HILDA Data Names:

Disposable Income: _TIFDIP, _TIFDIN, _TIFDIF, summed over household members, in AUS$;
Mobility: _HHMOVEK, in kilometers;
Value of Primary Residence: _HSVALUE, in AUS$;
Expenditure on Household Appliances: _HXYWGI, in AUS$.

Year	Description	NSW/ ACT	QLD	SA/NT	VIC/TAS	WA	Overall
2007	Energy Efficiency	2.70	2.74	2.81	2.79	2.71	2.74
	Loading Capacity	6.99	6.95	6.91	6.97	6.90	6.96
	Number of SKUs	154	149	107	152	131	190
	Price	747	742	744	768	764	753
	Revenue (Dollars)	178,855	142,289	52,440	142,303	77,463	593,350
	Sales (Units)	239,539	191,853	70,496	185,218	101,340	788,446
2008	Energy Efficiency	2.99	3.02	3.11	3.01	3.01	3.01
	Loading Capacity	7.01	6.96	6.99	6.95	6.94	6.97
	Number of SKUs	172	163	123	165	142	200
	Price	755	735	752	773	746	753
	Revenue (Dollars)	188,313	142,403	55,055	154,241	79,907	619,919
	Sales (Units)	249,279	193,675	73,166	199,615	107,090	822,825
2009	Energy Efficiency	2.95	2.92	2.97	2.98	2.92	2.95
	Loading Capacity	7.22	7.19	7.17	7.21	7.18	7.22
	Number of SKUs	143	141	110	139	130	164
	Price	789	733	784	751	751	776
	Revenue (Dollars)	184,812	125,555	53,821	153,867	72,487	590,542
	Sales (Units)	234,099	171,334	68,674	190,522	96,548	761,177

Table 2: Average Attributes and Revenue of Clothes Washers, by State.

Notes:
1. Attributes, including price, volume weighted averaged over all products;
2. Price given in AUS$;
3. Revenue given in '000s of AUS$;
4. "Overall" are weighted averages (by unit sales), models are total unique models available;
5. *Source:* GfK Australia and New Zealand.

State Acronyms:

NSW/ACT: New South Wales/Australian Capital Territory;
QLD: Queensland;
SA/NT: South Australia/Northern Territory;
VIC/TAS: Victoria/Tasmania;
WA: Western Australia.

	2007		2008		2009	
	Units	Share	Units	Share	Units	Share
By Brand:						
BOSCH	58,513	7%	64,950	8%	50,934	6%
ELECTROLUX	45,063	6%	76,537	9%	61,461	8%
FISHER&PAYKEL	179,316	23%	149,502	18%	141,049	19%
LG	138,099	18%	121,119	15%	114,383	15%
SAMSUNG	65,794	8%	72,024	8%	90,181	12%
SIMPSON	130,164	17%	153,916	19%	156,054	21%
TRADE BRAND	52,477	7%	41,098	5%	27,717	4%
WHIRLPOOL	52,848	7%	75,665	9%	65,819	9%
Other	66,172	8%	68,015	8%	53,578	7%
By Loading Capacity:						
$\leq$ 7kg	456,384	58%	472,248	57%	406,078	53%
$>$ 7kg	332,061	42%	350,577	43%	355,099	47%
By Energy Efficiency:						
$\leq$ 3 stars	370,735	47%	308,057	37%	365,703	48%
$>$ 3 stars	417,711	53%	514,768	63%	395,473	52%

Table 3: Clothes Washer, Unit Sold and Shares.

	Homogenous Model			Heterogenous Model		
	Estimate	Std Err	T-Stat	Estimate	Std Err	T-Stat
Variance						
σ_{ϵ_e}	1.147	0.019	59.750	1.380	0.023	59.068
$\rho_{\epsilon_c,\epsilon_e}$	0.257	0.067	3.809	0.007	0.034	0.220
σ_{ω_c}				0.207	0.055	3.795
σ_{ω_e}				0.559	0.029	19.261
ρ_{ω_c,ω_e}				-0.256	0.118	-2.174
Consideration Equation						
$\bar{c}_0$	-2.873	0.170	-16.906	-2.949	0.184	-16.029
λ	0.469	0.024	19.691	0.421	0.032	13.206
Disposable Income	0.195	0.016	12.234	0.202	0.005	11.751
Value of Primary Residence	0.017	0.002	8.208	0.018	0.002	8.030
Distance Moved	0.068	0.010	6.756	0.069	0.010	6.588
Expenditure Equation						
$\bar{e}_0$	3.066	0.344	8.915	3.971	0.287	13.826
γ	0.045	0.006	7.114	0.025	0.005	4.692
Disposable Income	0.249	0.026	11.141	0.207	0.026	7.986
Value of Primary Residence	0.030	0.003	8.827	0.026	0.003	7.348
Distance Moved	0.081	0.014	5.684	0.060	0.014	4.335

Table 4: Results, Category Expenditure Model.

Notes:
1. State and year fixed effects excluded (for brevity);
2. LL (homogenous) = -15,100, LL (heterogenous) = -14,740, with $\chi^2 = -2\Delta LL$ = 719.

Linear parameters:

Variable	Parameter Estimate	Std Err	T-Stat
Intercept	-0.102	0.073	1.389
Price	-0.930	0.014	-354.124
Energy Efficiency	0.267	0.002	145.839
Loading Capacity	-0.339	0.012	-29.112

Non-linear parameters:

	Heterogeneity			Category Expenditure		
Variable	Parameter Estimate	Std Err	T-Stat	Parameter Estimate	Std Err	T-Stat
Intercept	0.000	0.325	0.062	-12.062	0.721	-16.729
Price	0.217	0.014	15.727	-2.095	0.129	-16.280
Energy Efficiency	-0.000	0.123	0.004	-0.024	0.059	-0.402
Loading Capacity	0.307	0.018	16.898	3.461	0.033	104.31

Table 5: Results, Model of Clothes Washer Choice.

Description	Factor HD	HA	HM
Average Household Category Consideration Quasi Elasticity	0.20	0.02	0.07
Average Household Category Expenditure Elasticity	0.21	0.02	0.07
Average Household Clothes Washer Quasi Elasticity	0.67	0.06	0.23

Table 6: Elasticities, by Macro Socio-economic Factor.

Notes:

1. Elasticities are averaged across all households in all 5 states, in 2009,
2. Clothes washer quasi elasticities are averaged across products available for purchase,
3. HD: Disposable income,
4. HA: Value of primary residence,
5. HM: Distance Moved.

#		NSW/ ACT	QLD	SA/NT	VIC/ TAS	WA	Total
1	HN (#)	1,360	1,292	6,274	3,461	633	13,021
	HE ($)	1,719	1,763	7,914	4,566	952	16,914
	CW (#)	227	262	519	222	100	1,330
	CW ($)	179	192	406	179	75	1,032
2	HN (#)	-1,279	-806	-2,104	-2,974	-429	-7,592
	HE ($)	-2,319	-1,493	-3,329	-5,441	-1,036	-13,618
	CW (#)	-226	-85	-34	-87	-73	-505
	CW ($)	-179	-62	-27	-70	-55	-392
3	HN (#)	-17,606	-10,903	-28,104	-35,861	-5,415	-97,890
	HE ($)	-22,830	-14,721	-32,720	-48,898	-9,514	-128,683
	CW (#)	-2,019	-951	-69	-525	-729	-4,292
	CW ($)	-1,593	-696	-54	-424	-548	-3,314
4	HN (#)	3,901	2,368	7,101	8,213	1,176	22,760
	HE ($)	3,925	2,663	6,669	8,512	1,530	23,299
	CW (#)	16	13	-199	-461	-8	-639
	CW ($)	13	9	-156	-372	-6	-512
5	HN (#)	-8,867	-5,377	-15,143	-18,784	-2,754	-50,923
	HE ($)	-10,182	-6,681	-15,955	-23,269	-4,327	-60,415
	CW (#)	-374	-157	201	337	-204	-197
	CW ($)	-295	-115	158	272	-153	-133
6	HN (#)	308	-80	518	860	125	1,731
	HE ($)	-54	-467	-525	-516	-38	-1,599
	CW (#)	-29	-83	-208	-336	-43	-698
	CW ($)	-23	-61	-163	-271	-32	-549

Table 7: Impact on Household Appliance and Clothes Washer Sales, by Scenario.

Notes:
1. HN (#): Incease in number of households purchasing household appliances;
2. HE ($): Increase in total expenditure on household appliances, in ’000s of AUS$;
3. CW (#): Increase in clothes washers sales, in units;
4. CW ($): Increase in clothes washers sales, in ’000s of AUS$.

	Scenario:					
	1	2	3	4	5	6
Intercept	-0.534	0.806	25.671	-8.701	18.554	0.013
	2.730	0.673	4.852	1.844	3.388	0.493
Brands:						
BOSCH	-1.729	1.125	1.207	1.220	-0.632	0.404
	2.713	0.480	4.137	1.652	2.858	0.331
ELECTROLUX	-1.681	0.976	1.179	1.344	-0.975	0.389
	2.713	0.480	4.132	1.650	2.852	0.332
FISHER&PAYKEL	-1.665	1.098	1.611	1.209	-0.775	0.353
	2.713	0.478	4.122	1.650	2.848	0.332
LG	-1.703	0.972	1.518	1.237	-0.892	0.317
	2.713	0.477	4.125	1.648	2.849	0.330
SAMSUNG	-1.642	0.926	0.968	1.420	-1.138	0.367
	2.713	0.480	4.125	1.648	2.849	0.330
SIMPSON	-1.745	0.960	1.145	1.213	-0.766	0.224
	2.714	0.482	4.137	1.655	2.858	0.334
WHIRLPOOL	-1.687	0.984	1.432	1.267	-0.860	0.302
	2.713	0.482	4.134	1.651	2.853	0.334
Other	-1.719	1.009	1.609	1.261	-0.950	0.195
	2.713	0.480	4.116	1.649	2.843	0.331
Attributes:						
Energy Efficiency	0.088	0.147	0.842	0.897	-1.835	0.180
	0.101	0.147	0.721	0.288	0.554	0.122
Loading Capacity	0.327	-0.268	-4.135	1.137	-2.673	-0.020
	0.043	0.070	0.374	0.117	0.254	0.051
Energy Efficiency x Loading Capacity	-0.019	-0.011	0.008	-0.140	0.301	-0.026
	0.015	0.022	0.110	0.041	0.078	0.017
Diagnostics:						
Adj R^2	0.681	0.653	0.893	0.670	0.777	0.255
$F_{11,152}$	32.606	28.876	124.077	31.100	52.719	6.064

Table 8: WLS of Share Percentage Change, Projected on Product Attributes.

		Bosch	Electrolux	F&P	LG	Samsung	Simpson	Tradebrand	Whirlpool
1	PD (#)	98	120	227	198	167	268	46	112
	MS (#)	-214	22	-249	164	-12	25	412	73
	CW (#)	-116	141	-22	362	155	293	457	185
	CW ($)	-99	110	-16	317	99	192	396	124
2	PD (#)	-33	-40	-93	-76	-61	-102	-19	-46
	MS (#)	224	-34	302	-220	9	2	-440	-68
	CW (#)	191	-74	208	-297	-52	-100	-459	-113
	CW ($)	164	-57	155	-260	-33	-66	-397	-76
3	PD (#)	-263	-329	-802	-647	-516	-884	-165	-394
	MS (#)	1,373	-910	2,190	-1,738	-44	783	-2,969	-1,266
	CW (#)	1,111	-1239	1,388	-2,385	-560	-100	-3,134	-1,660
	CW ($)	952	-966	1,030	-2,093	-358	-66	-2,712	-1,116
4	PD (#)	-57	-62	-115	-95	-72	-122	-20	-47
	MS (#)	-61	424	-234	262	81	-451	209	518
	CW (#)	-118	362	-349	167	9	-573	188	471
	CW ($)	-101	282	-259	147	6	-375	163	317
5	PD (#)	4	-4	-41	-28	-25	-53	-12	-31
	MS (#)	429	-713	863	-766	-85	710	-1,047	-918
	CW (#)	432	-717	823	-794	-110	657	-1,059	-948
	CW ($)	371	-559	611	-697	-70	430	-916	-638
6	PD (#)	-57	-64	-124	-103	-81	-139	-23	-54
	MS (#)	151	132	88	-8	9	-150	-110	113
	CW (#)	94	68	-36	-111	-73	-289	-133	59
	CW ($)	81	53	-27	-98	-46	-189	-115	40

Table 9: Impact on Clothes Washer Demand, by Brand.

Notes:

By definition, PD + MS = CW, where:

1. PD (#): Increase in clothes washer sales due to primary demand effect, in units;
2. MS (#): Increase in clothes washers sales due to a substitution effect, in units;
3. CW (#): Total increase in clothes washers sales, in units;
4. CW ($): Total increase in clothes washers sales, in '000s of AUS$.

	Electrolux	F&P	Samsung	Simpson	Tradebrand	Whirlpool	
PD (#)	-4	-41	-25	-53	-12	-31	
MS (#)	-713	863	-85	710	-1,047	-918	
CW (#)	-717	823	-110	657	-1,059	-948	
Attribute levels:							Overall
Energy Efficiency	3.85	2.48	2.68	2.69	2.92	2.32	2.93
Loading Capacity	7.43	6.75	7.04	6.86	9.5	7.47	7.16
Price	779	742	639	654	865	672	786

Table 10: Primary Demand and Substitution Effect, by Brand, in Scenario 5.

Notes:

1. For brevity, a subset of brands is presented (excluding LG and Bosch);
2. Volume weighted average attribute, across products, in 2009, by brand;
3. Prices in AUS$.

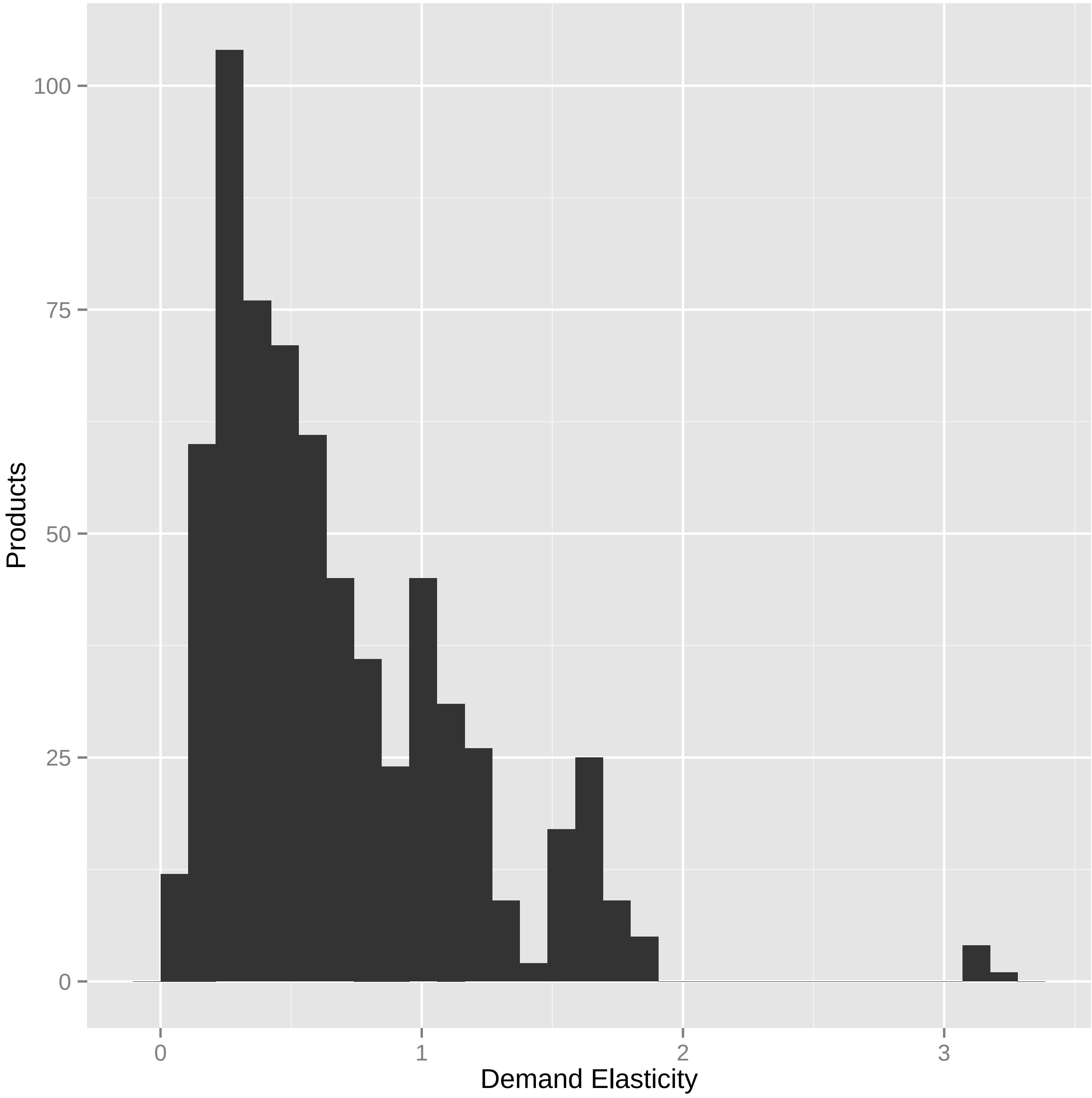


Figure 1: Histogram of Average Household Clothes Washer Quasi Elasticities, with respect to Disposable Income.

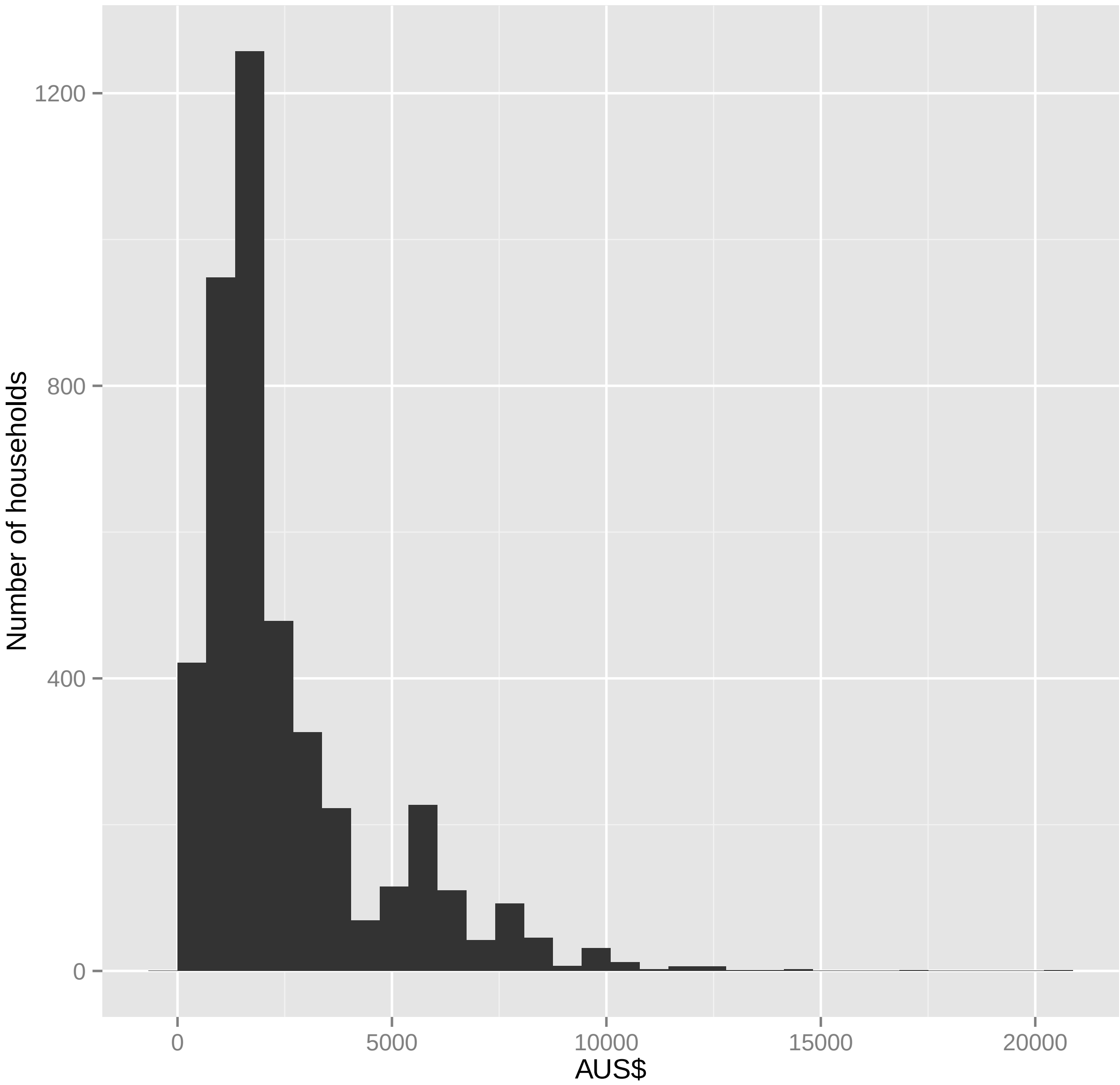
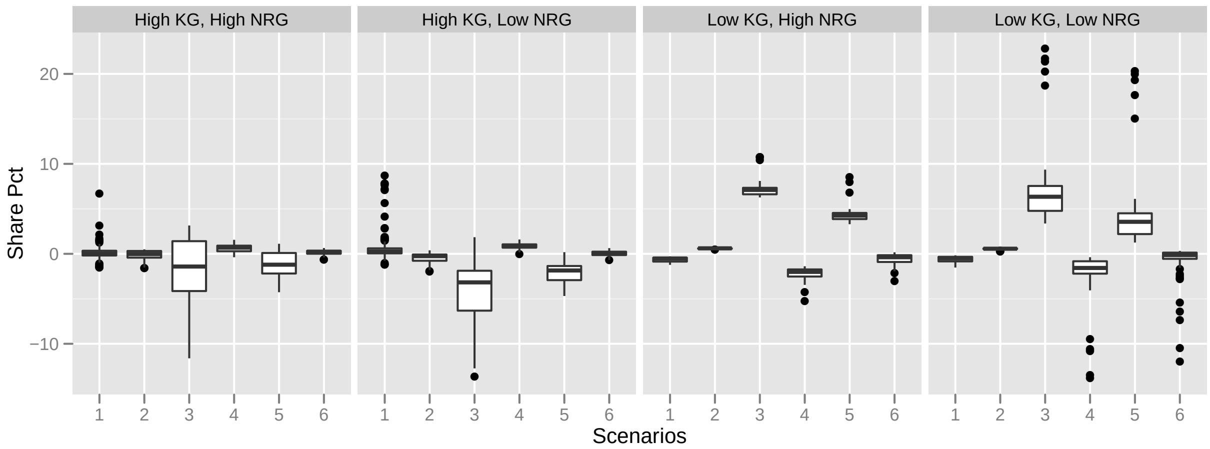


Figure 2: Histogram of Government Stimulus Payments.

(a) Product shares aggregated by attributes



(b) Product shares aggregated by brand

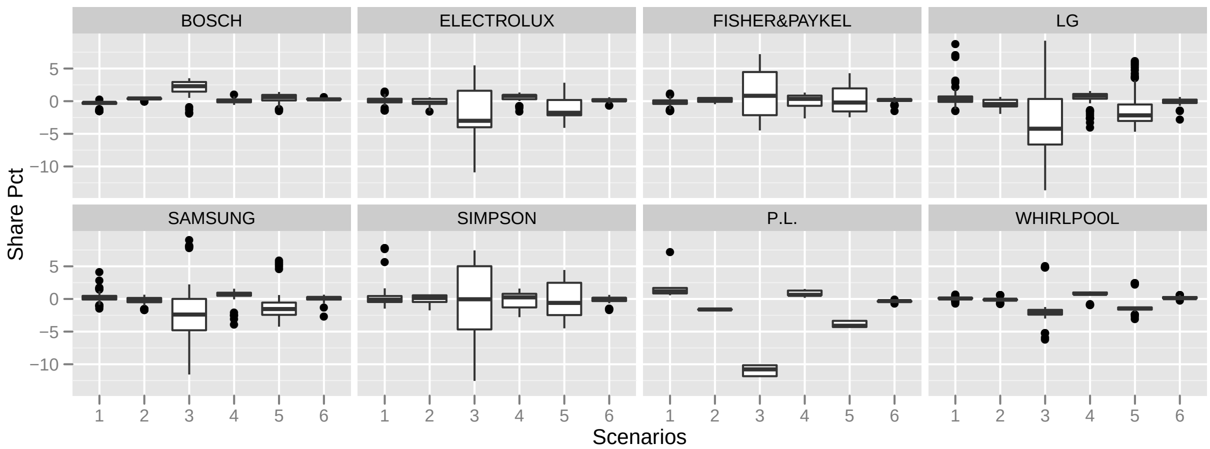


Figure 3: Share Changes, by Scenario and Product.

Appendix A: Properties of the category expenditure model

Rewrite the consideration and expenditure equations, combining ω_h and ϵ_h in equations (1) and (2):

$$\begin{aligned}
c^*_{hst} &= \lambda c_{hst-1} + z_{chst}\theta_c + D_{cst} + \omega_{ch} + \epsilon_{chst} = \Psi_{chst} + (\omega_{ch} + \epsilon_{chst}) \\
e_{hst} &= \begin{cases} \gamma e_{hst-1} + z_{ehst}\theta_e + D_{est} + \omega_{eh} + \epsilon_{ehst} = \Psi_{ehst} + (\omega_{eh} + \epsilon_{ehst}), & \text{if } c^*_{ht} \geq 0 \\ 0, & \text{if } c^*_{ht} < 0 \end{cases}
\end{aligned}$$

for $\Psi_{chst} = \lambda c_{hst-1} + \theta_c z_{chst} + D_{cst}$, and $\Psi_{ehst} = \gamma e_{hst-1} + \theta_e z_{esht} + D_{est}$ (where $c_{hst} = 1 \Leftrightarrow c^*_{hst} \geq 0$). The triplet $\{c_{hst}, z_{chst}, z_{ehst}\}$ is observed, while e_{hst} is observed only if $c_{hst} = 1$. We assume that $\{\epsilon_{chst}, \epsilon_{ehst}\}$ is independent of $z_{hst} = \{z_{ehst}, z_{chst}\}$, and $\sigma_{\epsilon_c} = 1$ in Σ_ϵ, with ω conditionally independent of ϵ. The distribution for the combined unobservable component $(\omega + \epsilon)$ is the bivariate normal :

$$\begin{aligned}
\Sigma_{\omega+\epsilon} &= \begin{bmatrix} 1 + \sigma^2_{\omega_c} & \rho_{\omega_c,\omega_e}\sigma_{\omega_c}\sigma_{\omega_e} + \rho_{\epsilon_c,\epsilon_e}\sigma_{\epsilon_e} \\ \rho_{\omega_c,\omega_e}\sigma_{\omega_c}\sigma_{\omega_e} + \rho_{\epsilon_c,\epsilon_e}\sigma_{\epsilon_e} & \sigma^2_{\omega_e} + \sigma^2_{\epsilon_e} \end{bmatrix} \\
&= \begin{bmatrix} 1 + \sigma^2_{\omega_c} & \rho\sqrt{(1+\sigma^2_{\omega_c})(\sigma^2_{\omega_e} + \sigma^2_{\epsilon_e})} \\ \rho\sqrt{(1+\sigma^2_{\omega_c})(\sigma^2_{\omega_e} + \sigma^2_{\epsilon_e})} & \sigma^2_{\omega_e} + \sigma^2_{\epsilon_e} \end{bmatrix},
\end{aligned}$$

where the total correlation (ρ) is:

$$\rho = \frac{\rho_{\epsilon_c,\epsilon_e}\sigma_{\epsilon_e} + \rho_{\omega_c,\omega_e}\sigma_{\omega_c}\sigma_{\omega_e}}{\sqrt{(1+\sigma^2_{\omega_c})(\sigma^2_{\epsilon_e} + \sigma^2_{\omega_e})}}.$$

$$
\begin{aligned}
Pr(c_{hst} = 1 \mid z_{hst}) &= Pr(c^*_{hst} > 0 \mid z_{hst}) \\
&= Pr(\Psi_{chst} + (\omega_{ch} + \epsilon_{ch}) > 0) \\
&= Pr((\omega_{ch} + \epsilon_{ch}) > -\Psi_{chst}) \\
&= 1 - \Phi\left(\frac{-\Psi_{chst}}{\sqrt{1+\sigma^2_{\omega_c}}}\right) = \Phi\left(\frac{\Psi_{chst}}{\sqrt{1+\sigma^2_{\omega_c}}}\right). \qquad (17)
\end{aligned}
$$

The conditional expectation of a bivariate normal random variable $(X, Y) \sim BVN(0, \Sigma_{X,Y})$, is $E[X \mid Y] = E[X] + \rho\frac{\sigma_X}{\sigma_Y}(Y - E[Y])$. Thus, expected category expenditure (conditional on household descriptors and unobservables in the consideration equation) is:

$$
\begin{aligned}
E[e_{hst} \mid z_{hst}, \omega_{ch} + \epsilon_{chst}] &= \Psi_{ehst} + E[\omega_{eh} + \epsilon_{ehst} \mid z_{hst}, \omega_{ch} + \epsilon_{chst}] \\
&= \Psi_{ehst} + E[\omega_{eh} + \epsilon_{ehst}] \\
&\quad + \rho\frac{\sqrt{1+\sigma^2_{\omega_c}}}{\sqrt{\sigma^2_{\omega_e} + \sigma^2_{\epsilon_e}}}\left((\omega_{ch} + \epsilon_{chst}) - E[\omega_{ch} + \epsilon_{chst}]\right) \\
&= \Psi_{ehst} + \rho\frac{\sqrt{1+\sigma^2_{\omega_c}}}{\sqrt{\sigma^2_{\omega_e} + \sigma^2_{\epsilon_e}}}\left(\omega_{ch} + \epsilon_{chst}\right). \qquad (18)
\end{aligned}
$$

Applying iterative expectations on $\omega_{ch} + \epsilon_{chst}$, the expected expenditure (conditional on descriptors and category consideration) is:

$$
E[e_{hst} \mid z_{hst}, c_{hst} = 1] = \Psi_{ehst} + \rho\frac{\sqrt{1+\sigma^2_{\omega_c}}}{\sqrt{\sigma^2_{\omega_e} + \sigma^2_{\epsilon_e}}}E[\omega_{ch} + \epsilon_{chst} \mid z_{hst}, c_{hst} = 1]. \qquad (19)
$$

Using Theorem 20.2 from Greene (2000):

$$
\begin{aligned}
E[\omega_{ch} + \epsilon_{chst} \mid z_{hst}, c_{hst} = 1] &= \sqrt{\sigma^2_{\omega_e} + \sigma^2_{\epsilon_e}} \left[\frac{\phi\left(-\Psi_{chst}/\sqrt{1+\sigma^2_{\omega_c}}\right)}{1 - \Phi\left(-\Psi_{chst}/\sqrt{1+\sigma^2_{\omega_c}}\right)} \right] \\
&= \sqrt{\sigma^2_{\omega_e} + \sigma^2_{\epsilon_e}} \left[\frac{\phi\left(\Psi_{chst}/\sqrt{1+\sigma^2_{\omega_c}}\right)}{\Phi\left(\Psi_{chst}/\sqrt{1+\sigma^2_{\omega_c}}\right)} \right].
\end{aligned}
$$

Define $a_{hst} = \Psi_{chst}/\sqrt{1+\sigma^2_{\omega}}$, where $\Lambda = \phi/\Phi$ is the inverse Mills Ratio, to get:

$$
E[e_{hst} \mid z_{hst}, c_{hst} = 1] = \Psi_{ehst} + \rho\sqrt{1+\sigma^2_{\omega_c}}\Lambda(a_{hst}). \tag{20}
$$

As $\mathrm{Var}[x] = \mathrm{E}[(x - \mathrm{E}[x])(x - \mathrm{E}[x])]$ and given independence of ω_h and ϵ_{hst} (see Bierens 2007):

$$
\mathrm{Var}[e_{hst} \mid z_{hst}, c_{hst} = 1] = \sigma^2_{\omega_e} + \sigma^2_{\epsilon_e} - \rho^2(\sigma_{\omega_e} + \sigma_{\epsilon_e})^2 \Lambda(a_{hst})\left(a_{hst} + \Lambda(a_{hst})\right).
$$

Appendix B: Derivation of elasticities with respect to a socio-economic driver

Category consideration quasi elasticity. Let z_{rhst} be an element of the vector z_{hst} expressed in logarithmic scale. The derivative of $P(c_{hst} = 1 \mid z_{hst})$ with respect to z_{rhst} is:

$$
\frac{\partial P(c_{hst} = 1 \mid z_{hst})}{\partial z_{rhst}} = \frac{\partial \Phi\left(\frac{\Psi_{chst}}{\sqrt{1+\sigma^2_{\omega_c}}}\right)}{\partial z_{rhst}} = \frac{\partial \Phi\left(a_{hst}\right)}{\partial z_{rhst}} = \frac{\theta_{cr}}{\sqrt{1+\sigma_{\omega_c^2}}}\phi\left(a_{hst}\right), \tag{21}
$$

where $a_{hst} = \frac{\Psi_{chst}}{\sqrt{1+\sigma_{\omega_c^2}}}$. Given $\Lambda = \phi/\Phi$ is the inverse Mills Ratio, the household-level category consideration quasi elasticity is

$$
\eta_{P(c_{hst}=1|z_{hst}), z_{rhst}} = \frac{|\theta_{cr}|\phi\left(a_{hst}\right)}{\sqrt{1+\sigma_{\omega_c^2}}\Phi\left(a_{hst}\right)} = \frac{|\theta_{cr}|\Lambda\left(a_{hst}\right)}{\sqrt{1+\sigma_{\omega_c^2}}}.
$$

Category expenditure elasticity. Taking derivatives of (20), we get

$$\begin{aligned}
\frac{\partial E[e_{hst} \mid z_{hst}, c_{hst}=1]}{\partial z_{rhst}} &= \frac{\partial}{\partial z}\left(\Psi_{ehst} + \rho\sqrt{1+\sigma^2_{\omega_c}}\Lambda(a_{hst})\right) \\
&= \theta_{er} + \rho\sqrt{1+\sigma^2_{\omega_c}}(-\Lambda(a_{hst}))(a_{hst}+\Lambda(a_{hst}))\frac{\theta_{cr}}{\sqrt{1+\sigma^2_{\omega_c}}} \\
&= \theta_{er} - \rho\theta_{cr}\Lambda(a_{hst})(a_{hst}+\Lambda(a_{hst})). \qquad (22)
\end{aligned}$$

Assuming that e_{hst} is expressed in logarithmic scale, the conditional category expenditure elasticity, conditional on category consideration, is:

$$\eta_{E[e_{hst}|z_{hst},c_{hst}=1],z_{rhst}} = |\theta_{er} - \rho\theta_{cr}\Lambda(a_{hst})(a_{hst}+\Lambda(a_{hst}))|. \qquad (23)$$

Quasi elasticity of purchasing product j. Differentiate the conditional probability $P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst}=1)$ with respect to z_{rhst}:

$$\begin{aligned}
\frac{\partial P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst}=1)}{\partial z_{rhst}} &= P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst}=1) \\
&\quad \left(\frac{\partial \mu_{hjst}}{\partial e_{hst}} - \sum_{k=1}^{J} P(k \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst}=1)\frac{\partial \mu_{hkst}}{\partial e_{hst}}\right) \\
&\quad \times \frac{\partial E[e_{hst} \mid z_{hst}, c_{hst}=1]}{\partial z_{rhst}}.
\end{aligned}$$

Replace for $\frac{\partial \mu_{hjst}}{\partial e_{hst}}$ to get:

$$\begin{aligned}
\frac{\partial P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst}=1)}{\partial z_{rhst}} &= P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst}=1) \\
&\quad \left(\sum_{r=1}^{R} \kappa_{er}\Delta x_{jrst} + \kappa_{ep}\Delta p_{jst}\right)\frac{\partial E[e_{hst} \mid z_{hst}, c_{hst}=1]}{\partial z_{rhst}}, \qquad (24)
\end{aligned}$$

where

$$\Delta x_{jrst} = x_{jrst} - \sum_{k=1}^{J} P(k \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst}=1)x_{krst},$$

and

$$\Delta p_{jst} = p_{jst} - \sum_{k=1}^{J} P(k \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst} = 1) p_{kst},$$

are mean-centered deviations (arithmetic mean, weighted by the conditional probability of purchase of each product) of the focal product's attribute r and price respectively. If $\frac{\partial E[e_{hst}|z_{hst}, c_{hst}=1]}{\partial z_{rhst}} > 0$, as in our application, then the conditional quasi elasticity of product j, conditional on category consideration, is:

$$\eta_{P(j|\mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst}=1), z_{rhst}} = \left| \left(\sum_{r=1}^{R} \kappa_{er} \Delta x_{jrst} + \kappa_{ep} \Delta p_{jst} \right) \right| \eta_{E[e_{hst}|z_{hst}, c_{hst}=1], z_{rhst}}. \tag{25}$$

The probability of household h buying product j is:

$$P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}) = P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst} = 1) P(c_{hst} = 1 \mid z_{hst}).$$

The derivative of this expression with respect to z_{rhst} is:

$$\begin{aligned}\frac{\partial P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst})}{\partial z_{rhst}} &= P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst} = 1) \frac{\partial P(c_{hst} = 1 \mid z_{hst})}{\partial z_{rhst}} \\ &\quad + P(c_{hst} = 1 \mid z_{hst}) \frac{\partial P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst} = 1)}{\partial z_{rhst}}.\end{aligned}$$

If $\frac{\partial P(c_{hst}=1|z_{hst})}{\partial z_{rhst}} > 0$ and $\frac{\partial E[e_{hst}|z_{hst},c_{hst}=1]}{\partial z_{rhst}} > 0$ as in our application, then it follows:

$$\begin{aligned}
\frac{\partial P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst})}{\partial z_{rhst}} &= P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst}=1) \frac{\theta_{cr}}{\sqrt{1+\sigma^2_{\omega_c}}} \phi\left(\frac{\Psi_{chst}}{\sqrt{1+\sigma^2_{\omega_c}}}\right) \\
&\quad + P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst}=1) P(c_{hst} \mid z_{hst}) \\
&\quad \left(\sum_{r=1}^{R} \kappa_{er}\Delta x_{jrst} + \kappa_{ep}\Delta p_{jst}\right) (\theta_{er} - \rho\theta_{cr}\Lambda(a_{hst})(a_{hst} + \Lambda(a_{hst}))), \\
&= P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst}=1) \\
&\quad \left[\frac{\theta_{cr}\phi(a_{hst})}{\sqrt{1+\sigma^2_{\omega_c}}} + \eta_{E[e_{hst}|z_{hst},c_{hst}=1],z_{rhst}} \Phi(a_{hst}) \right. \\
&\quad \left. \times \left(\sum_{r=1}^{R} \kappa_{er}\Delta x_{jrst} + \kappa_{ep}\Delta p_{jst}\right)\right], \\
&= P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}) \\
&\quad \left[\frac{\theta_{cr}\Lambda(a_{hst})}{\sqrt{1+\sigma^2_{\omega}}} + \eta_{E[e_{hst}|z_{hst},c_{hst}=1],z_{rhst}} \left(\sum_{r=1}^{R} \kappa_{er}\Delta x_{jrst} + \kappa_{ep}\Delta p_{jst}\right)\right],
\end{aligned}$$

$$\begin{aligned}
\frac{\partial P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst})}{\partial z_{rhst}} &= P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}) \left[\eta_{P(c_{hst}=1|z_{hst}),z_{rhst}} + \right. \\
&\quad \left. \eta_{E[e_{hst}|z_{hst},c_{hst}=1],z_{rhst}} \left(\sum_{r=1}^{R} \kappa_{er}\Delta x_{jrst} + \kappa_{ep}\Delta p_{jst}\right)\right].
\end{aligned} \tag{26}$$

The quasi elasticity of product j with respect to z_{rhst} (conditional on observed product attributes and prices, household observables, and heterogeneity) is:

$$\eta_{P(j|\mathbf{x}_{st},\mathbf{p}_{st},\nu_{hst},z_{hst}),z_{rhst}} = \left|\eta_{P(c_{hst}=1|z_{hst}),z_{rhst}} + \eta_{E[e_{hst}|z_{hst},c_{hst}=1],z_{rhst}} \left(\sum_{r=1}^{R} \kappa_{er}\Delta x_{jrst} + \kappa_{ep}\Delta p_{jst}\right)\right|.$$

Appendix C: Impact of a socio-economic driver on price elasticity

Define $Pr_{jhst} = P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst})$, $Pr_{jhst|c_{hst}} = P(j \mid \mathbf{x}_{st}, \mathbf{p}_{st}, \nu_{hst}, z_{hst}, c_{hst}=1)$, $Pr_{c_{hst}} = P(c_{hst}=1 \mid z_{hst})$, and $\eta_E = \eta_{E[e_{hst}|z_{hst},c_{hst}=1],z_{rhst}}$. Differentiate these with respect to

p_{jst}:

$$\begin{aligned}
\frac{\partial Pr_{jhst|c_{hst}}}{\partial p_{jst}} &= Pr_{jhst|c_{hst}}\left(1 - Pr_{jhst|c_{hst}}\right)(\alpha + \kappa_\alpha \nu_{h\alpha} + \kappa_{ep} e_{hst}),\\
\frac{\partial Pr_{jhst}}{\partial p_{jst}} &= Pr_{c_{hst}} \frac{\partial Pr_{jhst|c_{hst}}}{\partial p_{jst}}\\
&= Pr_{jhst}\left(1 - Pr_{jhst|c_{hst}}\right)(\alpha + \kappa_\alpha \nu_{h\alpha} + \kappa_{ep} e_{hst}),\\
\eta_{P(j|\mathbf{x}_{st},\mathbf{p}_{st},\nu_{hst},z_{hst}),p_{jst}} &= \left(1 - Pr_{jhst|c_{hst}}\right)|\alpha + \kappa_\alpha \nu_{h\alpha} + \kappa_{ep} e_{hst}|. \qquad (27)
\end{aligned}$$

If $\frac{\partial E[e_{hst}|z_{hst},c_{hst}=1]}{\partial z_{rhst}} > 0$, as in our application, and $sgn\,(x)$ is a step function indicating the sign of x, then from (22) and (24) we get:

$$\begin{aligned}
\frac{\partial \eta_{P(j|\mathbf{x}_{st},\mathbf{p}_{st},\nu_{hst},z_{hst}),p_{jst}}}{\partial z_{rhst}} &= \left(1 - Pr_{jhst|c_{hst}}\right) sgn\,(\alpha + \kappa_\alpha \nu_{h\alpha} + \kappa_{ep} e_{hst})\\
&\quad \kappa_{ep} \frac{\partial E[e_{hst} \mid z_{hst}, c_{hst} = 1]}{\partial z_{rhst}} - \frac{\partial Pr_{jhst|c_{hst}}}{\partial z_{rhst}} |\alpha + \kappa_\alpha \nu_{h\alpha} + \kappa_{ep} e_{hst}|,\\
&= \left(1 - Pr_{jhst|c_{hst}}\right) sgn\,(\alpha + \kappa_\alpha \nu_{h\alpha} + \kappa_{ep} e_{hst})\, \kappa_{ep} \eta_E\\
&\quad - Pr_{jhst|c_{hst}} \left(\sum_{r=1}^{R} \kappa_{er} \Delta x_{jrst} + \kappa_{ep} \Delta p_{jst}\right) \eta_E |\alpha + \kappa_\alpha \nu_{h\alpha} + \kappa_{ep} e_{hst}|. \qquad (28)
\end{aligned}$$