Otago Farmers Market:

An Empirical Analysis of Possible Pathways to Growth

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Abstract

The Otago Farmers Market, held in Dunedin, New Zealand, is one of the key outlets in the region where consumers can purchase food grown in the local area directly from producers. This dissertation uses a survey of 137 Otago Farmers Market customers from 2015 to build a descriptive model of preferences for local food that is relevant to real-world markets and the policy parameters that affect it. We find the mean premium customers are willing to pay for Otago produce compared to non-Otago New Zealand produce ranges between at least 2.1% and eight percent. Using a range of empirical models, we analyse how customer demographics, food shopping behaviours, and attitudes toward the Otago Farmers Market affect their shopping behaviour at the market as well as their willingness to pay a premium for local production of food. We find older people and people with higher income are consistently more favourable of the Otago Farmers Market and local food across these models. Being from outside of Dunedin, having purchased ready-to-eat food or drinks, and considering time to be a barrier to spending more at the market are negatively associated with variables across these two sets of outcome variables. Interestingly, shopping at the Otago Farmers Market because the products are local is strongly positively associated with a willingness to pay for local production of food, but not with annual spend at the Otago Farmers Market.

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1 Introduction

The number of farmers markets in New Zealand (NZ) increased from only one to more than 30 in the ten years from 1997 to 2007 (Cameron, 2005). One reason for the increasing number of farmers markets is concern among consumers about the social impacts of their purchases, such as for supporting their local economies. Guthrie, et al. (2006) also argue such development is driven by shifts in consumer attitudes from favouring convenience to quality. Reflecting this, Lawson et al. (2008) observe that vendors at farmers markets in NZ tend to be small businesses that compete against larger food sellers, mostly by taking advantage of their relative agility in meeting consumer tastes more quickly and effectively than large grocery stores.

Consumers' food preferences are far from static. Anticipating how consumers might respond to an expansion of the availability of local food, and building a descriptive model of preferences for local food that is relevant to real-world markets and the policy parameters that affect it, are among the primary motivations for this dissertation. The data used in this study is from a survey of 137 customers of the Otago Farmers Market (OFM) in Dunedin, NZ. OFM consists of a variety of food and plant stalls that come together to sell their wares on Saturday mornings. Vendors are required to be a to be the producer of their own products and to be from the surrounding region (Otago Farmers Market, 2015), making it one of the key places in Dunedin to buy locally produced foods direct from the producer. While there is always contextual specificity in studies of a single market, we believe there is at least some external validity allowing our findings to be of interest further afield.

Understandings gained in this study will be highly relevant to nearly all stakeholders in the food supply chain as they face changing consumer tastes. Farmers markets and other direct sales opportunities has been observed by local food advocates to be a lifeline for small agricultural producers, many of whom have been squeezed out of the grocery market (Cameron, 2007). Hence, an increased understanding of this niche market will be useful to such producers. Conventional food producers and retailers also have an opportunity to capitalise on increasing consumer value for local food by adapting appropriately.

In addition, increased knowledge of consumer interests within this topic will be useful to policy makers developing programmes to support local food systems (Low, et al., 2015) such as those of the U.S. Department of Agriculture (see United States Department of Agriculture, 2015). Interests for local food in the political realm of NZ have been seen in examples including The Ministry for Primary Industries grant from its 2014 Sustainable Farming Fund to the Otago

Local Food Economy Project. In an email to the authors, Lawton (September 23, 2015), a steering group member of the project, explained the aim of this project is to research potential economic opportunities of local food economies in Otago. It supports the ministry's objectives to 'deliver economic, environmental and social benefits to New Zealand' (Ministry for Primary Industries, 2015).

This dissertation focuses on two empirical questions. First, what influences individual customers' shopping behaviour measured in expenditures and shopping frequencies at OFM in the course of a year? Second, which among the potentially observable characteristics of shoppers measured in the survey data are most strongly associated with willingness to pay (WTP) a premium for domestically-produced food versus foreign-produced, and that for a local versus non-local domestic food (holding all other product attributes constant)? For both of these areas of research we consider the influences of demographic characteristics, food shopping behaviours and attitudes toward OFM.

Three dependent variables serve as primary measures of shopping behaviour at OFM: the individual's estimated annual spend on food at OFM[1]; the proportion of the individual's household's total annual food spending spent at OFM; and a binary variable for whether the individual is a frequent (i.e. weekly or near-weekly) shopper versus occasional shopper at OFM. Annual spend is modelled using ordinary least squares (OLS), with some further tests of robustness and a two stage least squares (2SLS) approach to account for potential endogeneity of variables relating to items purchased at OFM. A fractional Probit model is used for the OFM proportion of the individual's food budget to account for this variable's boundedness (between zero and one). Lastly, the probability of shopping weekly is estimated using a Probit model reported using average marginal effects.

To investigate influences on the consumers' valuation of local production as an attribute to a food product, we report the empirical distributions of the premiums and some further modelling of the premium that (some) customers would hypothetically pay for a more 'local' product. When estimating the premium measure for WTP for a domestically produced food item compared to an imported item, a large concentration of individuals with zero WTP for the foreign product have to be accounted for using Tobit estimation. We then apply a Chow test of whether the variables that influence consumers' WTP for local food do so following a

[1] From here on in this dissertation, measures of spend at the OFM (in either a single visit or over the course of a year) will refer to spend *on food*. The survey measured both total spend and spend on food in a visit to the OFM. We find that 93.8% of the total spend was on food.

common conditional mean function (as opposed to distinct conditional mean functions) for consumers willing and unwilling to purchase equivalent imported food items.

The results identify both challenges and opportunities for those seeking to expand OFM and its surrounding local food economies. The data show both older people and those with higher household income tend to be more committed OFM shoppers and place a larger subjective valuation on the localness of food. The subset of OFM consumers whose primary reason for being there is to enjoy its café culture (e.g. purchasing ready-to-eat food and drinks) are, quite predictably, less loyal patrons of OFM and have lower WTP for local food per se. Interestingly, favouring OFM because its products are local did not translate into a significantly higher annual spend but did increase the probability of shopping most frequently (i.e. weekly) and increase the proportion of the food budget directed toward OFM. Among the strongest predictors of being a high-frequency shopper are perceptions of advantages of OFM vendors in the areas of 'good service' and quality products. Unsurprisingly, respondents who mentioned time (i.e. limited hours in which the market is open) or bad weather as barriers to shopping at OFM were significantly less likely to shop as frequently or spend as much over a year. Results of the Chow Test suggest the way covariates affect the price customers would pay for a NZ product is no different for those willing and unwilling to buy a foreign but otherwise equal product, though this result is sensitive to model specification.

The remainder of this paper is arranged as follows. Section 2 comprises a review of previous literature. Section 3 describes the data used in empirical analyses and provides descriptive statistics and unconditional bivariate distributions in survey responses of key interest. The empirical models used are explained in Section 4 and main results are reported subsequently in Section 5. Section 6 contains a discussion and, finally, Section 7 a conclusion.

2 Previous Literature

Our review of previous literature is divided into separate sections covering studies on local food shopping behaviour and consumer WTP premiums for local food. We consider research that has focused on direct sales at farmers markets specifically (as in our study) as well as other data sources relating more broadly to consumer behaviour regarding local food.

2.1 Characteristics of Local Food Shoppers

Several descriptive analyses compare the characteristics of shoppers at farmers markets or those interested in local food relative to other food shoppers. Earlier studies suggest shoppers at farmers markets are more likely to be older, female consumers, with college educations and high levels of income (Eastwood, Brooker & Gray, 1999; Kezis et al., 1998). More recent research finds that demographic characteristics have less influence than they once did regarding associations with local food preferences, suggesting demand for local food is likely spreading across a wider range of consumers. Brown (2003) finds no significant difference among demographic characteristics of southeast Missouri consumers who sought products labelled as locally produced. In a Californian study, Wolf, Spittler and Ahern (2005) report that farmers market shoppers are more likely to be female and have postgraduate educations while finding few differences by age and income status.

Behaviours and attitudes among farmers market shoppers are compared by Brown (2003), Eastwood, Brooker and Gray (1999) and Kezis et al (1998). These studies reveal that farmers market shoppers have preferences that are unusually sensitive to product quality. Other distinguishing characteristics of shoppers at farmers markets noted in these previous studies include: having a farming background or parents who were raised on a farm; placing substantial weight on differences in freshness; having an interest in supporting local farmers; and prefering the friendly atmosphere. Associations of local and organic food with environmentalism would appear to be less strong than theory would predict. Perhaps surprisingly, for example, Brown (2003) finds that being a member of an environmental group was not associated with local food consumption. Eastwood, Brooker and Gray report that travel costs are among the most common deterrants that block consumers who would otherwise want to shop for local food at farmers markets.

Moving to a NZ context, Mirosa and Lawson (2012) compare shopping behaviours, attitudes and personalities of NZ consumers who make a strong effort to buy food locally with those who are observed to make no such effort. Tests of differences in means indicate local food shoppers are more likely to prefer fresh, organic, unprocessed and non genetically-modifed foods; they are also more interested in cooking, health, and product information that includes nutrition labelling. Murphy (2011) shows that shoppers in NZ who visit farmers markets at least monthly on average rated the following variables as significantly more important than did less frequent shoppers at farmers markets: quality produce, healthy food, seasonal produce, supporting the local community, and customer service. High prices appear to be among the biggest deterrents facing consumers who would otherwise want to do more of their shopping at farmers markets, followed by unattractive appearance of local food, the costs of parking and the disadvantagess of bad weather (relative to indoor shopping at grocery stores). Comparing farmers market shoppers and supermarket shoppers, the quality of products is reported by both types as being important, but significantly more so to farmers market shoppers.

Of particular interest to this study is how the characteristics and preferences of consumers influence variation in shopping behaviour. Effects of demographic characteristics in this context is somewhat inconsistent but generally have weak effects. For example, Onianwa, Wheelock, and Mojica (2005) use a Logit model on a sample of consumers from Alabama to estimate the likelihood of shopping for food directly from producers. Having education above high school level is associated with an 8.5 percentage-point increase in the probability of buying directly from local producers (relative to a base rate of 79%), and household income is positively associated but only for families with children. Their study shows that no other characteristics have statistically or economically significant effects. Some studies report even weaker results (e.g. sociodemographic characteristics having no significant effects on local food shopping in Eastwood, Brooker and Gray, 1999, and Keeling-Bond, Thilmany and Bond, 2009).

Zepeda and Li (2006) argue that behaviours and attitudes are more capable of explaining differences in local food shopping behaviour than demographics. They use a Probit model for a sample from a national survey of US food consumers where the outcome variable is whether consumers shopped at farmers markets, farm stands, or Community Supported Agriculture at least once a month. Sociodemographic variables are largely insignificant. Buying organic food, shopping at specialty stores, and gardening are the behaviours in their data that are positively associated with shopping for local food. Behaviours relating to cooking and physical exercise show no signifiant effects although positive effects of ‘enjoying cooking’ has a large positive effect. ‘Concerns about the cost of food’ has the opposite effect. The authors argue that enjoying cooking could be linked to a preference for fresher food, which would explain its positive effect on expected rates of shopping locally. Zepeda and Li (2006) report no significant effects for variables that theory would have predicted large effects for: nutrition and health, energy conservation, and ensuring that farmers receive sufficient prices are factors with no significant associations with the frequency of shopping for local food.

Some local food advocates point to the advantage of local food avoiding transport over long distances (i.e. lower ‘food miles') resulting in lower environmental costs (e.g. Thompson, Harper, & Kraus, 2008). However, one UK study finds that many who report an interest in minimising food miles do not feel intensely about it, or have enough information, to change their shopping behaviour (Kemp, et al., 2010). Kemp et al (2010) report that 25.1% of supermarket shoppers surveyed in the UK said they would not buy NZ products because of their large number of food miles. Yet, when unprompted about food miles, only 5.6% of those same consumers report that country of origin was a reason for having selected a produce item, and only 19.1% can correctly identify where items they purchased originated from. This apparent gap between expressed intentions and actual shopping behaviour appears in numerous other areas of research (Young, DeSarbo, & Morwitz, 1998). This gap is likely related to similar gaps between expressed intentions and attitudes on the one hand and costly behaviour on the other as reported in the study by Zepeda and Li (2006) described above.

Westervelt and Hawkins (1979) propose a psychological model based on Maslow's hierachy of needs in which farmers market shoppers (as consumers in well-to-do developed nations) have already satisfied their physiological needs and are likely to have moved toward satisfying higher needs including self-actualisation. According to the authors, their model predicts that consumers would shop at the market primarily to interact with vendors and other consumers. However, their research involving a survey of farmers market shoppers in Alberta, Canada, finds that indivdiuals described as pursuing self-actualisation were no more likely to shop at farmers markets. Instead, freshness of the products appears, once again in Westervelt and Hawkins' data, to be they key attraction.

Using logistic regression on a binary measure of being a local food shopper in NZ, Mirosa and Lawson (2012) find older and more educated consumers are more likely to make a strong effort to buy local food. They show that local food buyers typically are less concerned about appearance and social standard, they value family and careers more highly, and they are more environmentally and socially conscious than non-local food buyers. Local food shoppers in Mirosa and Lawson's data, once again, consider quality and service to be among the most important factors when shopping; these shoppers also appear to be more frugal and put more effort into shopping.

2.2 Consumer WTP a Premium for Local Production

An array of methods are used to model consumer WTP a premium for local production in the literature. Brown (2003) uses perhaps the simplest analysis, comparing those who would pay more for food labeled as grown locally to those who would not. Those willing are more likely to be females, higher income earners, residents of rural areas, buyers of organic food, members of environmental groups and have farming backgrounds. They are also slightly more likely to put the most value on quality when shopping for fruit and vegetables and less likely to value price the most.

Some studies have approached this research by estimating outcome variables in binary or ordinal categorical choices related to WTP a premium. A recent study of households in Al Ain City, United Arab Emirates, employs a Logit model for WTP a premium for locally produced poultry and eggs over imported products, conditional on individual sociodemographic characteristics (Fathelrahman, et al., 2015). The authors find the expected premium increases in household income and family size, and decreases in age, and females are less likely to be willing to pay a premium than males. An ordered Probit model of Hispanic consumers in east-coast U.S. is employed by Govindasamy and Puduri (2010), with outcome categories for willing, indifferent, or unwilling to buy locally grown produce that is usually imported (called 'ethnic' food). Eighty percent of the sample was willing to buy local food. Characteristics which increase the likelihood of being willing to buy local food include a willingness to buy organic, local, or new to the market produce; less concern for product packaging; a longer time living in the current location; having more children; and having higher incomes. Distance from an ethnic store, price, age, education and gender had no significant effects on willingness to buy local food.

Darby et al. (2007) ask direct food (including farmers market) and grocery store shoppers in Ohio to choose between several pairs of strawberries with different labeling of price, freshness, corporate affiliation and location of production. They estimate a random effects Probit model with the chosen product across two options as the outcome variable. Results show consumers at both shopping locations were willing to pay more for strawberries produced within the state or 'grown nearby' compared to food labelled as from the U.S. An estimated premium for local production of $0.92 for direct food shoppers was higher than that of $0.48 for grocery store shoppers, but in neither sub-sample did consumers value strawberries from Ohio or 'grown nearby' significantly differently. These premiums are estimated after controlling for product freshness and corporate affiliation (i.e. labelling the strawberries as produced by 'Fred's Berry Farm' versus 'Berries Inc.') which, Darby et al find, warrant their own premiums. This is a quite unique approach of the literature we have reviewed to separate components of local production which consumers value. No difference is found in the various premiums across demographic characteristics, except males at direct markets can be expected to pay more for local production than females.

We found only one study which estimates WTP for a food item using a continuous variable with location of production as a dependent variable. Gracia, de Magistris and Nayga (2012) use information from an experimental auction in Aragón, Spain, on consumer WTP a premium for locally produced lamb products in separate models for men and women. Using maximum likelihood they estimate WTP for the product conditional on whether it was labelled as local and individual characteristics. Males and women are both expected to pay a premium for local production, though this is higher for women.

2.3 Contribution of This Study

After searching Econlit, Google Scholar and other databases, it appears that this study can contribute to the relevant research literatures on shopping behaviour for local food and farmers markets in several ways. This study analyses dollar expenditure at a farmers market that, when combined with shopping frequency, provides a new imputed measure of annual expenditures at the farmers market over an entire year. We are unaware of any previous studies that use one-day expenditures and information about shopping frequency to construct an annual spend variable. This approach incorporates more information in the dependent variable and leads to more relevant analysis of which types of consumers are responsible for the greatest share of the farmers market's annual revenue. We also consider this annual spend measure relative to total food spending, which as far as we know, is novel in the context of the farmers market research literature. Another novel dependent variable that we consider is WTP for local food under several contrasting definitions and well-defined scenarios involving common products from specific countries and regions within NZ. An advantage of our analysis is that we use a continuous rather than a binary or ordinal outcome variable. We are not aware of any study in the extant literature which examines how such a rich set of consumer demographics, behaviours and attitudes are associated with a continuous outcome variable for WTP for local food production. We also compare the WTP a premium of domestic over imported products from two very different countries (China and the U.S.) to reveal whether this premium depends on the source country. Furthermore, we investigate whether consumers place additional value on Otago (i.e. the local region) over domestic production elsewhere in NZ.

3 Data

On the 28th of March, 2015, 114 OFM customers were interviewed onsite by 11 paid interviewers who were trained to follow a written script to structure and sequence survey items in a uniform manner.[2] In addition, cards were given out to OFM shoppers asking for online survey respondents (and advertised in OFM's March 2015 newsletter), which resulted in a further 23 online survey participants.

The dataset is cross-sectional and each observation corresponds to a unique respondent. We consider the onsite interviews to be representative of OFM customers on the day of the interview. Based on the interviewers' impressions we estimate the response rate of those invited to participate in the survey was one in three people. While this may sound low, given people are busy we did not expect a high participation rate. We made sure to have interviewers on site at all time periods, starting even before the official opening of the market, and they were scattered around the market to avoid selection bias. However, as there is no census of all shoppers to compare and cross-validate against, it is not possible to formally rule out selection bias.

The online survey is not representative owing to sample selection bias from being advertised in the newsletter, which is potentially likely to be distributed to people with a particular interest in OFM. It also phrased some questions slightly differently. For example, in the scripted interview we asked how much the individual had spent or planned to spend at the market, but in the online survey this was replaced with how much the individual *usually* spends at the market. For our main models we test for bias from this sub-sample.

3.1 Dependent Variables

The dependent variables summarised in Table 1 include several transformations and variations of the basic list of shopping behaviour outcomes that we are interested in: expenditures, shopping frequency, and WTP for more 'local' products. *Spend* measures (in units of NZ$) the expenditure at OFM on the day of the interview (or 'usual spend' at OFM among online respondents). This spend in a single visit together with information about the frequencies with which shoppers attend OFM are used to estimate annual spend, based on assumptions about frequency and the representativeness of the respondents' expenditures on the day in which they

[2] Appendix 8.1 contains the survey script our interviewers used in training and during the interviews themselves.

Table 1: Dependent Variables Definitions and Descriptive Statistics

Variable Name	Variable Definition
Spend	Dollar spend on food at OFM in single visit
AnnualSpend	Annual dollar spend at OFM
LnAnnualSpend	ln[(Annual spend at OFM) + 1]
PropAnnualSpend	Proportion of yearly household food budget spent at OFM
Weekly	1 if shops weekly at OFM, 0 otherwise
DiscountChina	(WTPNZ-WTPChina[1])/WTPNZ
DiscountUSA	(WTPNZ-WTPUSA[1])/WTPNZ
DiscountNZnonlocal	(WTPOtago[2] - WTPNZ) / (WTPOtago)
WTPNZ	Willingness to pay per kg for produce item if from NZ
LnWTPNZ	ln(WTPNZ)

1 - Where WTPChina is the willingness to pay per kg for chosen produce item if from China. 2 - Where WTPOtago is the willingness to pay per kg for chosen produce item if from Otago

were interviewed. Our survey item categorises shoppers as occasional, monthly, fortnightly and weekly shoppers. To estimate annual spend, we assume that: occasional shoppers visit OFM four times; monthly shoppers visit 10 times; fortnightly shoppers visit 24 times; and weekly shoppers visit 48 times per year (reflecting conservative assumptions about holidays, sick days, and unanticipated deviations from self-reported shopping frequency). *AnnualSpend* is computed by multiplying the assumed number of annual visits by *Spend*:

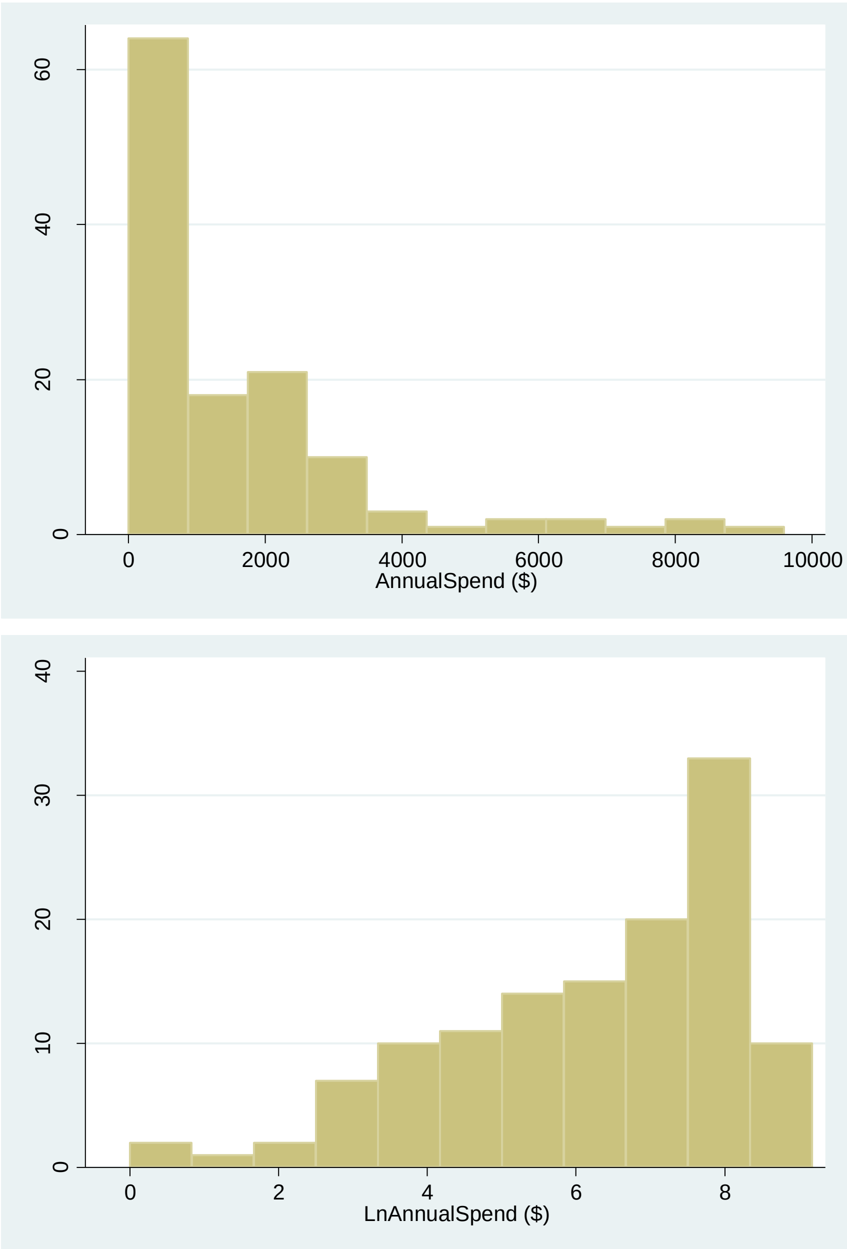
$$AnnualSpend = \begin{cases} 1 \times Spend & \text{if } Frequency = \text{First time (N = 13)} \\ 4 \times Spend & \text{if } Frequency = \text{Occasionally (24)} \\ 10 \times Spend & \text{if } Frequency = \text{Monthly (13)} \\ 24 \times Spend & \text{if } Frequency = \text{Fortnightly (13)} \\ 48 \times Spend & \text{if } Frequency = \text{Weekly (66)} \end{cases}$$

Figure 1 shows the highly skewed empirical distribution of *AnnualSpend* and the more evenly distributed empirical distribution of *LnAnnualSpend*, demonstrating that after applying the natural log transformation this expenditure variable's skew is attenuated, or somewhat reversed.

The variable *PropAnnualSpend* is computed as *AnnualSpend* divided by self-reported annual household food budget. The survey measure elicited from each respondent an estimated weekly household budget for food, including both unprepared and prepared (e.g. restaurant) food.[3] We

[3] We chose to measure the food budget at the household level rather than the individual level because households frequently pool resources such as food. Therefore, the conservative measurement approach suggests that we measure proportions of expenditures at OFM relative to an individual's household food expenditure rather than individual food expenditure. Interviewers were trained to explain our definition of household referred to those one shops with for food to ensure the measure has a consistent interpretation across individuals.

Figure 1: Distributions of AnnualSpend and LnAnnualSpend



multiplied responses to this survey item by 52 to approximate the household's annual food budget corresponding to each individual.

The shopping frequency variable, *Weekly*, is a binary indicator. We have more detailed information on shopping frequency as described earlier. However, because half the respondents are weekly shoppers and their expenditures make up the majority of OFM revenue, we argue that this coarsening of frequency into a binary state focuses the explanatory information on the most meaningful distinction.

WTPNZ measures responses to a survey item that elicited WTP for NZ grown produce.[4] Respondents were first asked if they ever buy lemons. If yes, then they were asked the maximum they would pay per kilogram for lemons from NZ. If they did not buy lemons, the survey proceeded to ask if they would buy oranges, garlic, and then tomatoes, stopping whenever they had a food item that the respondent would purchase, to ask their WTP for the item, given it came from NZ. If a respondent said that he or she would not buy any of the items, then *WTPNZ* records a missing value. We argue it is appropriate to collect values for different products in a single variable because it will always be compared relative to the valuation for the same product category from a different location. Figure 2 shows the empirical distribution of *WTPNZ* and its log transformation (*LnWTPNZ*) which we use in empirical models because it is significantly less skewed. Only 69 observations were valid due to difficulty experienced by interviewers in asking and by customers in answering questions on WTP, as well as the presence of some customers in the sample who never buy any of the above food items.[5]

Respondents were asked their WTP for the same product if, instead of being from NZ, had come from China, the U.S., or Otago (with otherwise equal observable quality attributes). We use this information to estimate each individual's implied valuation for more 'local' production across various comparisons of production location. The variables *DiscountChina* and *DiscountUSA* measure percentage discounts in WTP for Chinese and U.S. produced goods (lemons, oranges, garlic, or tomatoes), respectively, compared to a NZ product. Similarly, the variable *DiscountNZnonlocal* measures the percent discount in an individual's WTP for NZ (which could be from anywhere in the country) versus Otago produced food products.

The relatively high frequency of zero values of WTP for foreign produced food motivates our convention of measuring discounts, so that percentage changes can be computed relative to a non-zero base valuation. WTP for Otago and NZ are strictly positive in all cases.

The distributions of these variables are illustrated in Figure 3. The distributions of *DiscountChina* and *DiscountUSA* each exhibit a cluster of observations at the upper tail, comprised of individuals who apply a 100% discount to foreign-grown produce (i.e. zero WTP for 'otherwise identical' products grown in China or the U.S.) In contrast, the bottom-most histogram in Figure 3 of discounts applied to non-Otago relative to Otago-grown produce has no observations of 100% discount rates but has a large cluster of zero discounts.

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[4] See survey question 33 in Appendix 8.1.

[5] A binary indicator for whether *LnWTPNZ* is missing has a correlation greater than 10% with independent variables *LnHhIncome*, *Local*, and *Money* (defined below).

Figure 2: Distributions of WTPNZ and LnWTPNZ

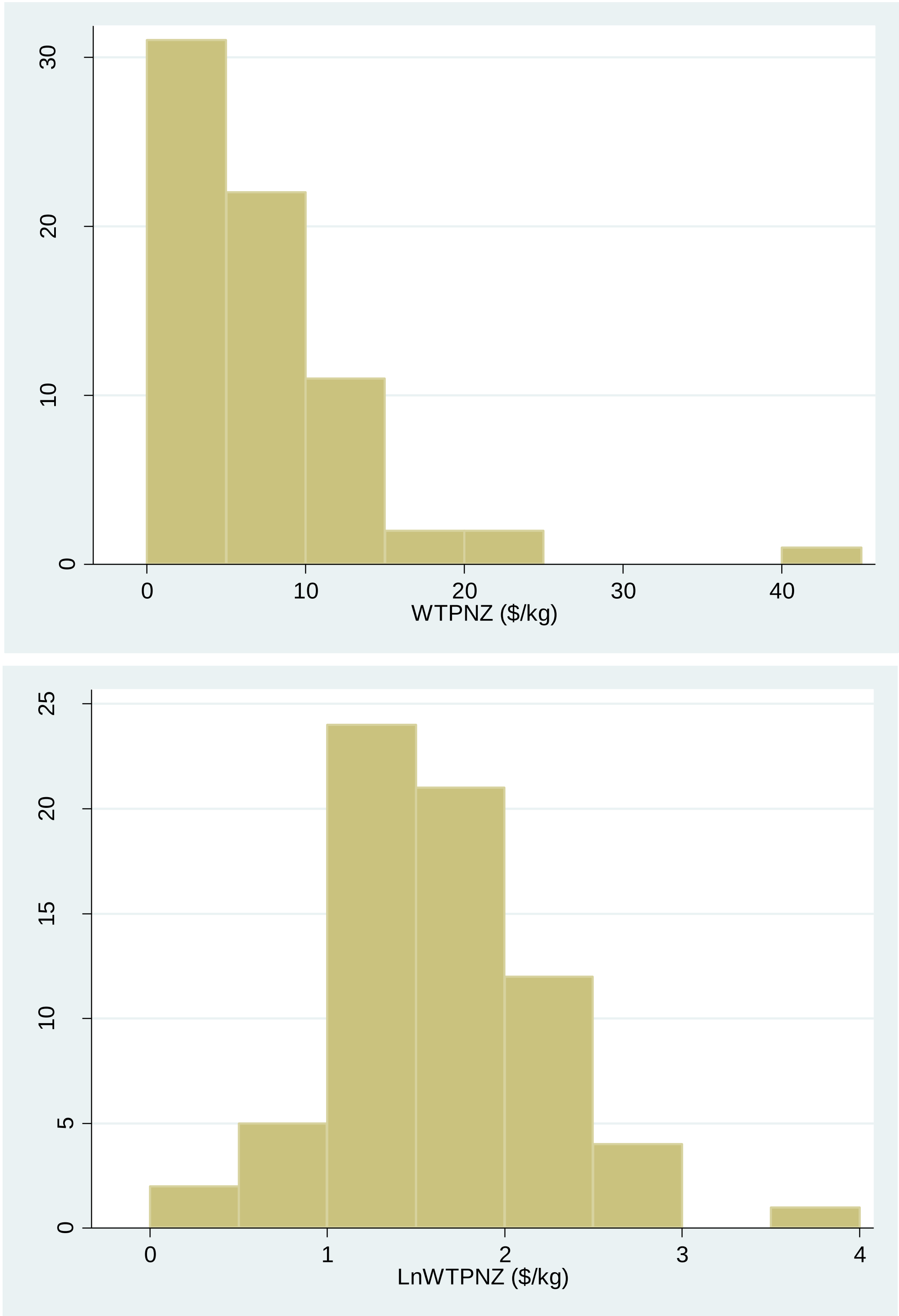


Figure 3: Distributions of DiscountChina, DiscountUSA and DiscountNZnonlocal

Table 2 below shows mean local premiums computed as within-person differences in WTP in dollar units. In all cases, the mean premiums are positive and significantly different from zero at the one percent level. The mean respondent is willing to pay more than $4.00 *more* for a kilo of NZ lemons (or oranges, tomatoes or garlic) than the same items grown in China or the U.S. The local premium for Otago versus non-Otago domestic produce is considerably smaller at $0.53 but sill large enough to achieve economic significance at moderate sales volumes. However, we prefer to use the percentage discount approach described above to account for the fact that several different products are being considered.

Table 2: Within-Person Differences in Willingness to Pay (WTP) for NZ v. China; NZ v. USA; Otago v. non-Otago-NZ

Difference	Mean ΔNZ$	Std. Error	Std. Dev	t	Obs.	P-value
WTPNZ - WTPChina	4.68	0.78	6.18	5.96	62	0.0000
WTPNZ - WTPUSA	4.36	0.83	6.40	5.23	59	0.0000
WTPOtago - WTPNZ	0.53	0.20	1.58	2.71	64	0.0086

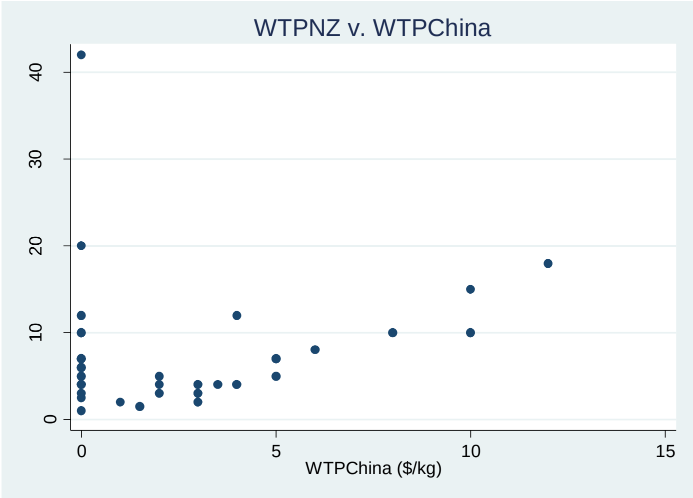
Figure 4 shows the bivariate empirical distribution of WTP as scatterplots of the three pairs of places of origin about which WTP was elicited. The first two scatterplots in Figure 4 show the cluster of individuals with effectively lexicographic preferences by which *WTPChina* or *WTPUSA* is zero, which implies infinite relative WTP for the NZ product). Although economists' standard preference specifications typically rules out such incommensurability by assuming utility functions that always allow for internal rates of substitution at some positive and finite relative price, our data provide evidence of a distinct segment of OFM consumers with precisely incommensurable views—that foreign produce is worth nothing and remains undesirable no matter how cheaply priced. In contrast, the subsample scattered around a finite-sloped bivariate regression line, whose slope is greater than 1, tends to view the NZ place of origin as worth paying a premium for. This split in the sample suggests that the mean premiums reported above in Table 2 were the weighted averages of two groups, both of which are willing to pay a premium for NZ products but with sharply contrasting willingnesses to trade off preferred places of origin against price.

The final scatterplot in Figure 4 shows no lexicographic clustering along the y-axis, as all respondents have strictly positive WTP for non-Otago produce grown in NZ. The bivarate regression line has a slope of 1.036, which implies that consumers in our sample were willing to pay, on average, a 3.6% premium for local food, defined as having been produced in the Otago region. We consider several other measures of calculating the average premium. The mean premium for Otago produce over NZ produce when computed as individual-level percentage-change premiums and then averaged over individuals is 7.6% (using the very same observations). The mean individual's premium is eight percent.[6] We also computed an unconditional elasticity (of *WTPOtago* with respect to non-Otago *WTPNZ*) as the slope of a bivariate regression of ln(*WTPOtago*) on ln(*WTPNZ*) which is 0.021. In other words, for every unit of value a consumer derives from a NZ food item, he or she receives an extra 2.1% from an otherwise similar item if it was produced in the Otago region.

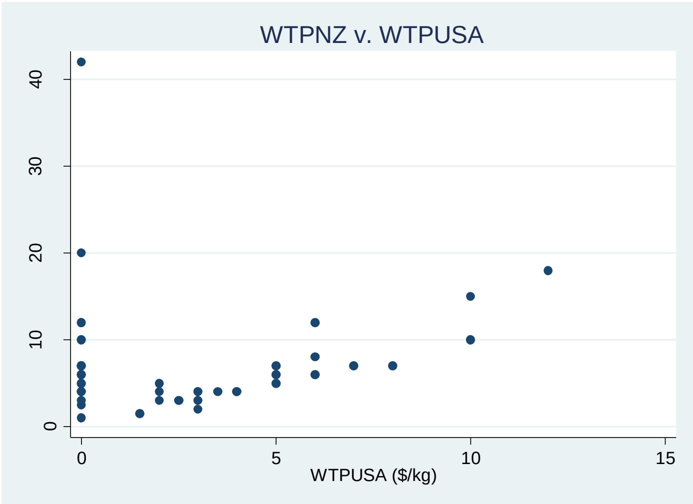
We will later use the discounts (i.e. *DiscountChina*, *DiscountUSA*, *DiscountNZnonlocal*) corresponding to the three pairings of places of origin and also *WTPNZ* as dependent variables to estimate fully conditional empirical models in the next section. We believe these two representations of the preference information are relevant for different reasons. Measures of discounts in WTP are in percentage units and bounded between -1 and 1, and we use them to investigate how individual characteristics are related to value for local production as an attribute of a food product. *WTPNZ* is in dollar units and is theoretically unbounded above and below. We use this variable to investigate whether there are differences in how the two subsamples of consumers identified earlier, those willing and those unwilling to buy foreign produce, evaluate a local food product.

[6] Given mean *WTPOtago* = \$7.17 and mean *WTPNZ* = \$6.64; 7.17/6.64 - 1 = 0.08.

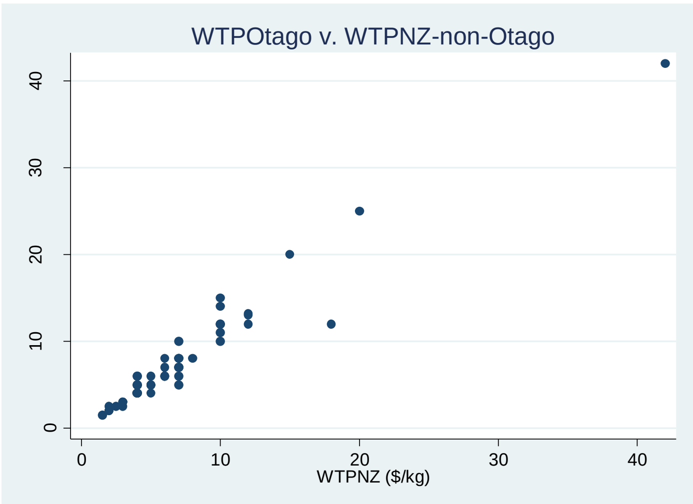
Figure 4: Bivariate Distribtions of WTP for Further (China, U.S. and non-Otago-NZ) and WTP for Closer (NZ, NZ and Otago) Places of Origin in an Otherwise Identical Food Item (lemons, oranges, garlic or tomatoes)



Bivariate regression slope = 1.257 where WTPChina > 0



Bivariate regression slope = 1.189 where WTPUSA > 0



Bivariate regression slope = 1.036

3.2 Independent Variables

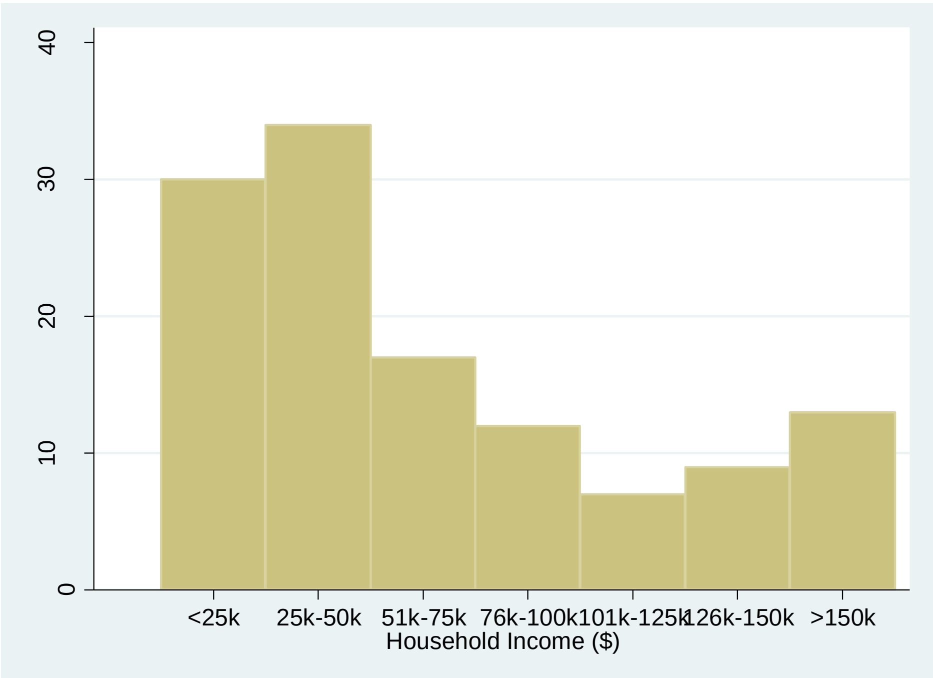
Table 3: Independent Variable Definitions

Variable	Variable Definition
Demographics	
Age	1 if aged 18 to 29, 2 if aged 30 to 49, 3 if aged 50 or older
Male	1 if male, 0 if female
University	1 if has graduated from university or has postgraduate qualifications, 0 otherwise
Hhincome	midpoint of household income categories which are (in thousands of dollars) '< 25', '25-50', '51-76-100', '100-125' and '> 150'
LnHhIncome	ln(Midpoint of dollar HhIncome category)
Adults	1 if one adult lives in household, 2 if two adults, 3 if three or more adults
Children	1 if children live in household, 0 otherwise
OutsideDunedin	1 if lives outside of Dunedin, 0 otherwise
Behaviours	
FreeRange	1 if shops at OFM for free range foods, 0 otherwise
Organic	1 if shops at OFM for organic foods, 0 otherwise
DrinksEating	1 if purchased drinks or food to eat outdoors
Attitudes	
Service	1 if friendly service or interaction with vendors is a reason for shopping at OFM, 0 otherwise
Quality	1 if quality of products is a reason for shopping at OFM, 0 otherwise
Fresh	1 if freshness of products is a reason for shopping at OFM, 0 otherwise
Local	1 if local is a reason for shopping at OFM, 0 otherwise
Atmosphere	1 if atmosphere is a reason for shopping at OFM, 0 otherwise
Prices	1 if prices is a reason for shopping at OFM, 0 otherwise
Time	1 if time is main barrier to spending more at OFM, 0 otherwise
Weather	1 if weather is main barrier to spending more at OFM, 0 otherwise
Money	1 if money is main barrier to spending more at OFM, 0 otherwise
WTP	
WTPChina	Willingness to pay per kg for chosen produce item if from China
LnWTPChina	ln(WTPChina +1)
WTPUSA	Willingness to pay per kg for chosen produce item if from USA
LnWTPUSA	ln(WTPUSA +1)
China_Positive	1 if WTPChina > 0, 0 if WTPChina = 0
USA_Positive	1 if WTPUSA > 0, 0 if WTPUSA = 0
Variables for Robustness checks	
Interviewer	Categorical variable to control for which interviewer conducted the interview
Hour	Hour interviewed between 7am and 12pm (for onsite interviewees only)
Online	1 if surveyed online, 0 if interviewed onsite at OFM

Main empirical models reported in the results section are run with successive encompassing specifications that add the first three italicized variable groups identifiable in Table 3, which lists all independent variables.

All models include the demographic variables in the first grouping of the explanatory variables listed in Table 3 (grouped into *Demographics*, *Behaviours* and *Attitudes*). The construction of *LnHhIncome* requires some more explanation than what can be inferred from Table 3. Our survey instrument recorded household income as a categorical variable whose empirical distribution appears in Figure 5. However, because its empirical distribution is highly skewed, the log transformation was applied. We took the midpoint measure of each income category recorded except for the final category ($150,000+) for which we used $150,000, before logging to compute the variable *LnHhincome***.** All other *Demographic* characteristics are coded as categorical variables.

Figure 5: Distribution of Household Income



Behaviours include indicators for whether the respondent states that he or she shops at OFM primarily for organic or free range foods, if they bought ready-to-eat food or drinks to consume at the market, or if they source local food other than from OFM.[7] We interpret the latter as a coarse proxy for the importance placed on local food as reflected in behaviour.

[7] We provided examples of sources of local food to respondents, which included food grown in one's own garden; local farm vendors; and food-boxes or co-operatives. Respondents were prompted to add any other local food sources they use.

Respondents were asked to name their top three reasons for shopping for food at OFM and the single top barrier preventing them from spending more at OFM, however some respondents listed more than the prompted number of reasons and barriers. All were coded as binary indicators which make up the *Attitudes* variables. Of particular note, *Service* incorporated responses showing preferences for the 'friendly' service of vendors, the possibility to 'interact' with them or to 'get to know' them. The variable *Local* envelopes both shopping at OFM because products are locally produced, and to support local farmers or businesses.

The *WTP* variable group is not added to all models. Log transformations of *WTPChina* and *WTPUSA* are included as independent variables in regressions of *LnWTPNZ* only (and each separately). *China_Positive* and *USA_Positive* are indicators relating to whether these variables are positive or zero, which are interacted with other conditional variables in the same models of *LnWTPNZ* to allow mapping to the different slopes across these groups.

Robustness tests which check for interviewer fixed effects and selection bias in online survey participants involve variables *Interviewer* and *Online*, respectively. *Hour* is also included in the interviewer fixed effects model to account for different times interviewers worked, given the hour at which the shopper was interviewed at OFM is clearly correlated with some of the other variables which, in turn, affect the dependent variables.

3.3 Summary Statistics

Table 4: Dependent Variable Descriptive Statistics

Variable Name	Obs	Mean	Std. Dev.	Min	Max
Spend	125	42.33	36.88	0.00	200.00
AnnualSpend	125	1495	1911	0	9600
LnAnnualSpend	125	6.17	1.94	0.00	9.17
PropAnnualSpend	115	0.214	0.220	0.000	0.923
Weekly	129	0.512	0.502	0.000	1.000
DiscountChina	62	0.621	0.458	-0.500	1.000
DiscountUSA	59	0.557	0.466	-0.500	1.000
DiscountNZnonlocal	64	0.048	0.151	-0.500	0.333
WTPNZ	69	6.84	5.93	1.00	42.00
LnWTPNZ	69	1.69084	0.66	0.00	3.74

Table 4 shows means, standard deviations and ranges of the dependent variables for the main empirical models, and additional ones reported in the appendix. *AnnualSpend* ranges from \$0 to \$9,600 with a mean of \$1,495, reflecting how skewed toward lower values its distribution is. The mean value of log transformations of *AnnualSpend* is more central than the original variable. The mean individual's proportion of the household food budget spent at the OFM was

21%, with variation from zero to 92% also suggesting a skewed distribution.[8] Just over half (51%) of respondents said they shopped at the market weekly.

The number of observations are not consistent across all variables because some respondents did not answer all questions. In particular interviewers had difficulty asking and customers difficulty responding to survey items on WTP. Variables to relating to WTP are also missing if the individual placed no positive value on lemons, tomatoes or garlic from any location. Hence there is a rapid decline in observations for these variables.[9]

We suspect online respondents were highly selected from the upper tail of the most loyal and highest spending OFM customers, owing to the selection bias issue described earlier. Table 5 therefore presents descriptive statistics broken out by in-person versus online survey responses, confirming our expectations.

Table 5: Dependent Variable Descriptive Statistics by Survey Method

	Onsite Interview			Online Survey		
Variable	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Spend	111	37.44	32.66	14	81.07	46.17
AnnualSpend	111	1289	1726	14	3124	2533
LnAnnualSpend	111	6.01	1.94	14	7.51	1.34
Weekly	114	0.50	0.50	15	0.60	0.51
PropAnnualSpend	102	0.201	0.217	13	0.319	0.224
DiscountChina	54	0.579	0.467	8	0.906	0.265
DiscountUSA	51	0.528	0.476	8	0.740	0.371
DiscountNZ	56	0.054	0.157	8	0.000	0.089
WTPNZ	60	6.90	6.28	9	6.44	2.83
LnWTPNZ	60	1.68	0.69	9	1.79	0.40

Table 6 summarises the independent variables from which conditional expectation functions are to be estimated. Some interesting points which we learn from the statistics in Table 6 include: ‘50+’ is the largest age category (where ’18 to 29’ year olds are the omitted reference class); our sample is more female than male with 37% of respondents being male, which we believe is representative of the population of OFM shoppers; a large portion, more than half of respondents have a university degree or postgraduate qualifications (61%), shop at OFM to buy free range foods (60%), shop at OFM for organic foods (56%), and get local food from other sources than OFM (69%); and almost a third (31%) buy drinks or ready-to-eat food at the

[8] While it might seem necessary then to apply a log transformation to *PropAnnualSpend*, this is not appropriate for the empirical model we use for this variable given it’s boundedness between 0 and 1.
[9] These explanations also apply to independent variables below, where numbers of observations also vary.

Table 6: Independent Variable Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Age = 30 to 49	128	0.297	0.459	0	1
Age = 50+	128	0.398	0.492	0	1
Male	126	0.373	0.486	0	1
University	128	0.609	0.490	0	1
Hhincome	122	60635	49073	12500	150000
LnHhIncome	122	10.64	0.91	9.43	11.92
Adults = 2	128	0.430	0.497	0	1
Adults = 3+	128	0.227	0.420	0	1
Outside Dunedin	128	0.125	0.332	0	1
FreeRange	128	0.602	0.492	0	1
Organic	128	0.563	0.498	0	1
DrinksEating	128	0.313	0.465	0	1
OtherLocal	127	0.685	0.466	0	1
Service	122	0.180	0.386	0	1
Quality	122	0.287	0.454	0	1
Fresh	122	0.516	0.502	0	1
Local	122	0.361	0.482	0	1
SupportLocal	122	0.262	0.442	0	1
Atmosphere	122	0.336	0.474	0	1
Prices	122	0.164	0.372	0	1
Time	117	0.171	0.378	0	1
Weather	117	0.308	0.464	0	1
Money	117	0.103	0.305	0	1
WTPChina	68	1.87	2.87	0.00	12.00
LnWTPChina	68	0.67	0.84	0.00	2.56
WTPUSA	65	2.48	3.22	0.00	12.00
LnWTPUSA	65	0.84	0.91	0.00	2.56
China_Positive	68	0.426	0.498	0	1
USA_Positive	65	0.492	0.504	0	1
Hour	101	9.60	1.44	7	12
Online	137	0.168	0.375	0	1

market.[10] The most popular reason for buying food at the market is freshness, which was mentioned by 52% of respondents. *Weather* is the most common barrier to spending more at the market, mentioned by 31%. The mean *WTPChina* is considerably lower than mean *WTPUSA*, and just less than half of respondents placed positive value on the foreign items.

[10] For online respondents, we consider someone as having drinks and prepared food if they report they 'would normally do so' when shopping at OFM.

Table 7 compares means across in-person and online sample respondents, which reveal large differences in independent variables across survey method.

Table 7: Independent Variable Descriptive Statistics by Survey Method

	Onsite Interview			Online Survey		
Variable	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Age = 30 to 49	113	0.292	0.457	15	0.333	0.488
Age = 50+	113	0.363	0.483	15	0.667	0.488
Male	111	0.387	0.489	15	0.267	0.458
University	113	0.593	0.493	15	0.733	0.458
Hhincome	107	57266	48111	15	84667	50814
LogHhincome	107	10.57	0.91	15	11.11	0.78
Adults = 2	113	0.398	0.492	15	0.667	0.488
Adults = 3+	113	0.248	0.434	15	0.067	0.258
OutsideDunedin	113	0.124	0.331	15	0.133	0.352
FreeRange	114	0.570	0.497	14	0.857	0.363
Organic	114	0.526	0.502	14	0.857	0.363
DrinksEating	113	0.310	0.464	15	0.333	0.488
OtherLocal	113	0.646	0.480	14	1.000	0.000
Service	110	0.164	0.372	12	0.333	0.492
Quality	110	0.273	0.447	12	0.417	0.515
Fresh	110	0.545	0.500	12	0.250	0.452
Local	110	0.364	0.483	12	0.333	0.492
SupportLocal	110	0.255	0.438	12	0.333	0.492
Atmosphere	110	0.327	0.471	12	0.417	0.515
Prices	110	0.182	0.387	12	0.000	0.000
Time	105	0.152	0.361	12	0.333	0.492
Weather	105	0.314	0.466	12	0.250	0.452
Money	105	0.114	0.320	12	0.000	0.000
WTPChina	60	2.07	2.98	8	0.38	1.06
LnWTPChina	60	0.73	0.86	8	0.17	0.49
WTPUSA	57	2.65	3.34	8	1.25	1.91
LnWTPUSA	57	0.88	0.93	8	0.53	0.76
China_Positive	60	0.467	0.503	8	0.125	0.354
USA_Positive	57	0.509	0.504	8	0.375	0.518

3.4 Hypotheses

Table 8 demonstrates the expected signs of the marginal effect of each of the independent variables on the expected value of our main empirical model of expenditure at OFM, as motivated by theory and previous research. A number of interesting effects are, we believe, theoretically indeterminate or have been found to go in both directions in different examples of previous literature, indicated by '?' in Table 8.[11] While we provide expectations for estimated direction of effects of demographic characteristics, insignificance of many of these variables would not be surprising given this has been the case in much of the more recent literature (e.g. Zepeda & Li, 2006).

Table 8: Expected Signs of Marginal Effects of Independent Variables on Expected Expenditure

Variables	Expected Effect
Age = 30 to 49	+
Age = 50+	+
Male	?
University	+
LnHhIncome	+
Adults = 2	+
Adults = 3+	+
OutsideDunedin	-
FreeRange	+
Organic	+
DrinksEating	-
LocalOther	+
Service	+
Quality	+
Fresh	+
Local	+
SupportLocal	+
Atmosphere	?
Prices	-
Time	-
Weather	-
Money	-

3.5 Descriptive Analysis

To motivate subsequent empirical models we provide further descriptive analysis of several bivariate patterns. Figure 6 shows a scatterplot of household income and *AnnualSpend*. The bivariate distribution shows large statistical variation with good numbers of observations on both sides of the mean *AnnualSpend* of $1289 within every category of household income

[11] We are unable to predict the direction of the effect of gender or of a preference for atmosphere, which could increase spend due to additional enjoyment of the OFM but decrease spend if it is associated with people visiting for occasional social outings rather than regular grocery shopping.

including the lowest. The bivariate regression line which would fit through the joint distribution in Figure 6 is weakly positive with mostly unexplained variance.

Figure 6: Bivariate Distribution of AnnualSpend and HhIncome

Figures 7a and 7b show six scatterplots of household income and *AnnualSpend* broken out by eight different binary survey items, with goal of visually demonstrating behaviours common to individuals in the far upper tail of the *AnnualSpend* distribution. These highest spenders all shop as frequently as possible (weekly) at OFM. Free range and organic shoppers and those who prefer local food from other sources also seem to cover the upper tail. In contrast, those who go to OFM for prepared food and drink and those for whom prices are a barrier to spending more are, consistent with intuition, negatively correlated with *AnnualSpend*. The final scatterplot at the bottom of Figure 7b highlights those who are concurringly *Weekly*, *Organic*, *FreeRange* and *OtherLocal* shoppers and do not favour *DrinksEating* or low *Prices*. This does a reasonably good job of identifying higher spending individuals in the distribution of *AnnualSpend*.

Table 9 presents the joint empirical distribution of *Weekly* and *DrinksEating* which shows evidence of the difference in products more frequent shoppers seek: 18% of weekly shoppers bought drinks or food to eat at the market compared with 45% of non-weekly shoppers. Differences in the empirical distributions of *Spend* on the day of the survey spend over a year (i.e. *AnnualSpend*) are observable among non-weekly versus weekly shoppers in Figure 8.

Figure 7a: Bivariate Distribution of AnnualSpend and HhIncome with Behavioural Indicators

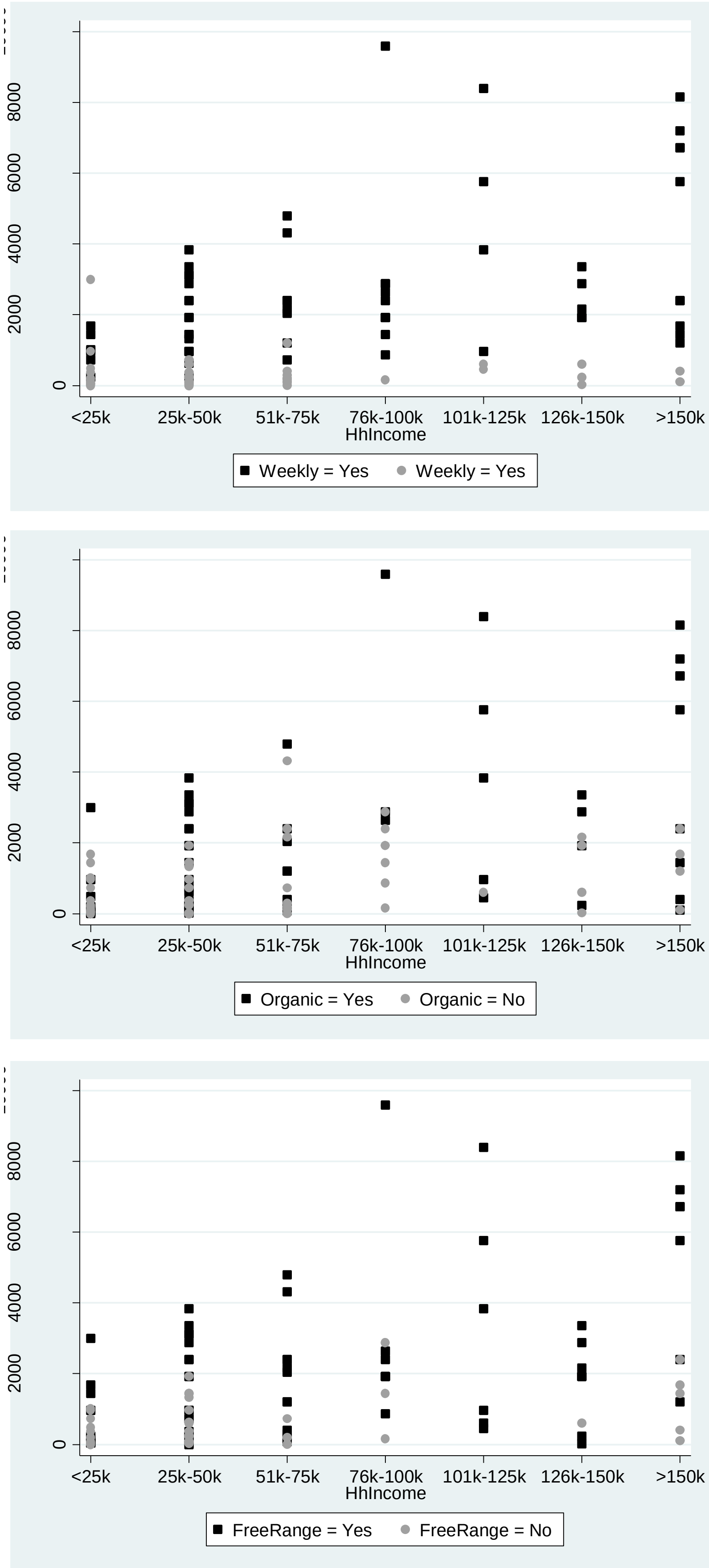


Figure 7b: Bivariate Distribution of AnnualSpend and HhIncome with Behavioural Indicators

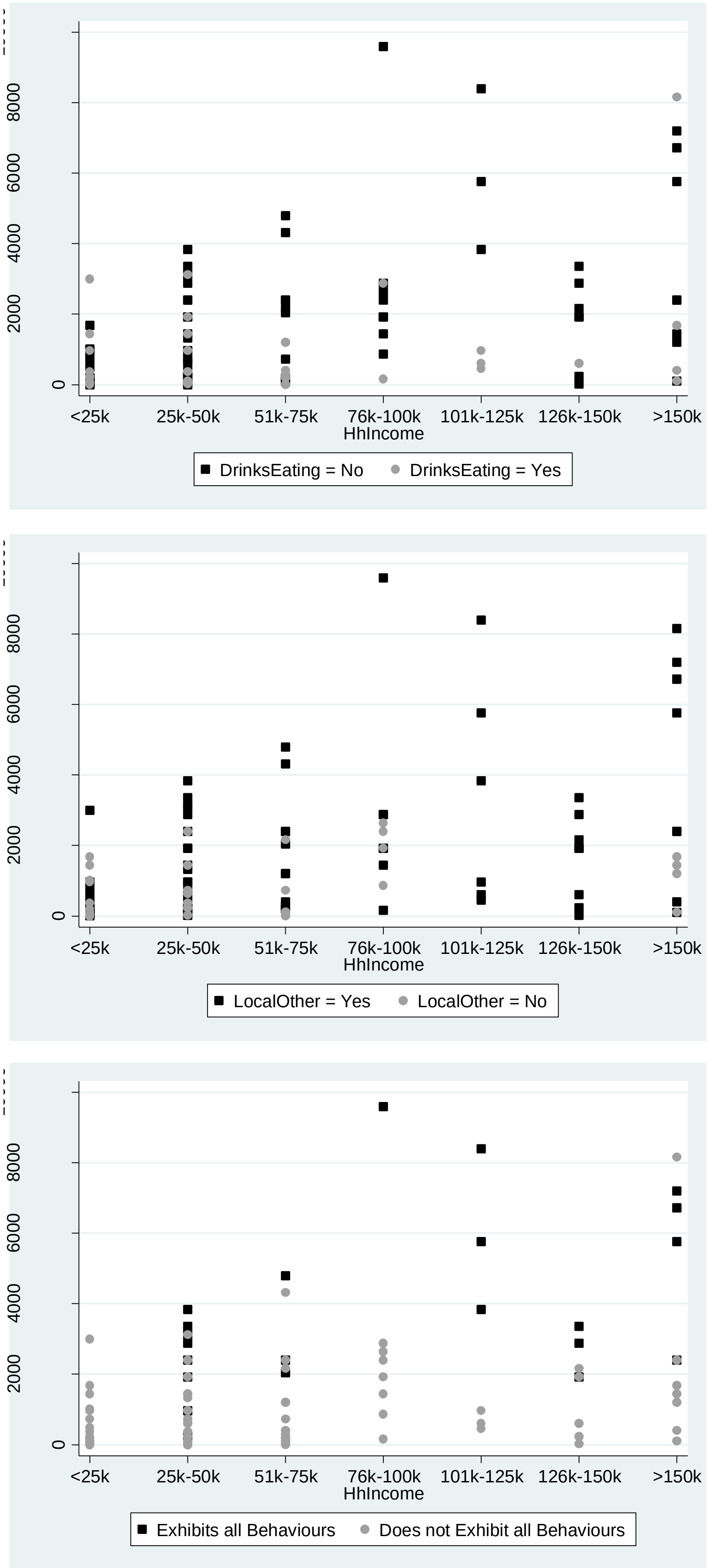
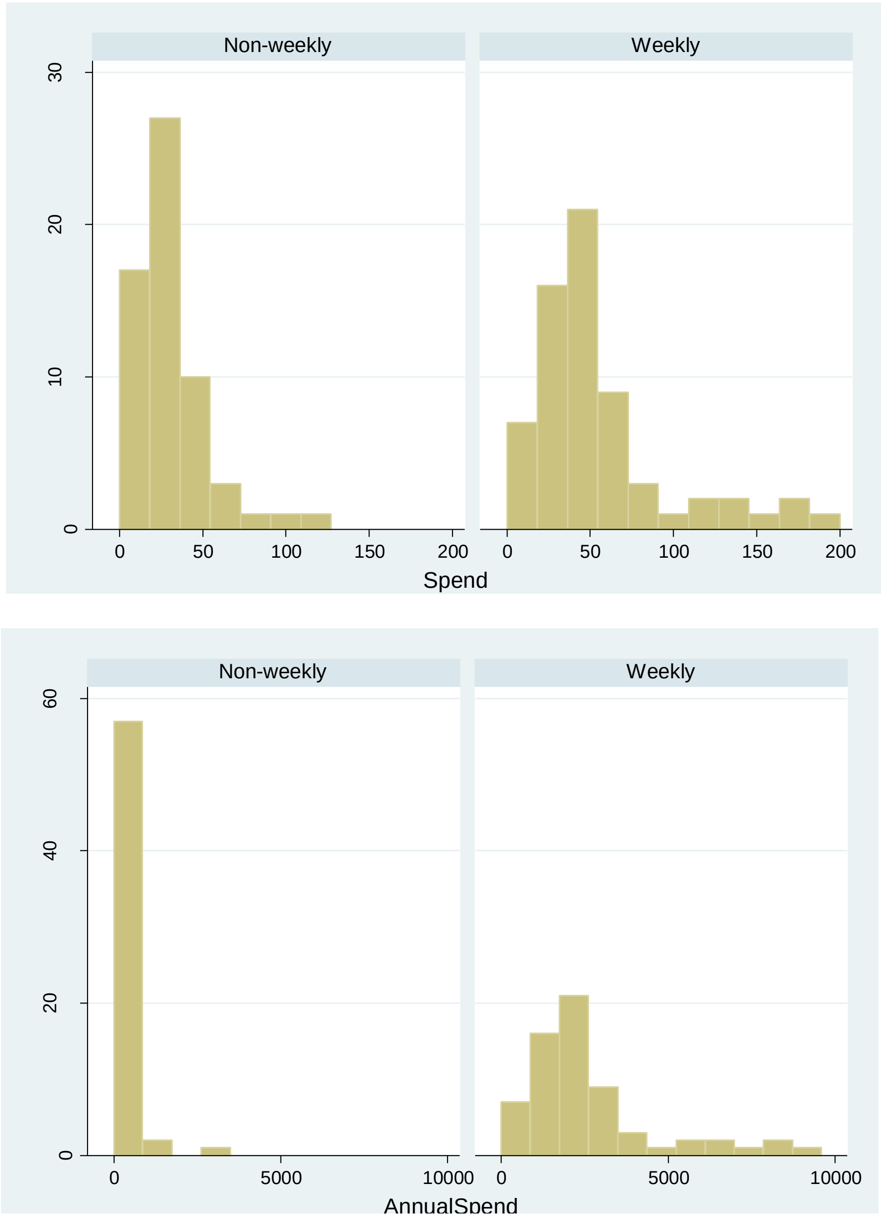


Table 9: Cross Tabulation of Weekly and DrinksEating

Weekly	DrinksEating No	DrinksEating Yes	Total
No	34 54.84%	28 45.16%	62 100%
Yes	54 81.82%	12 18.18%	66 100%
Total	88	40	128

Figure 8: Distribution of Non-Weekly Versus Weekly Shoppers' Spend and AnnualSpend



4 Empirical Method

We estimate our main empirical models by successively adding groups of variables, each one encompassing previous models, starting with the most basic model that includes only *Demographics* (referred to as Model 1 in the tables below); then adding variables measuring shopping behaviours, referred to as the *Behaviours* variables (Model 2); and finally, the *Attitudes* variables (Model 3). We report a number of alternative model specifications as robustness checks, most of which are relegated to the appendices. For example, we re-run Models 1-3 of our main dependent variable checking for interviewer effects and possible time-of-day effects following the same design but including *Interviewer* indicators and time-of-day variable *Hour* for reasons explained in section 3.2. For parsimony's sake given the relative small number of observations (and because we find no important differences when including them), we choose to not include interviewer fixed effects in the main models. While we note that hours by itself is predictive of spend, we do not want to attribute variance separately to the hours decision relative to other explanatory variables, as the goal of the study is to see how demographics, attitudes and observable regularities of shopping behaviour predict shopping behaviour e.g. if early shoppers come for organics that may sell out, then the organic dummy should tell us that rather than hours. It is worth noting that including *Hour* causes all information on online survey respondents to drop from regressions since this information could not be recorded for them.

Let $\boldsymbol{X}$ denote a vector that stacks each of the three groups of covariates mentioned above excluding a constant. The coefficients multiplying each element of $\boldsymbol{X}$ in the equations presented below are represented by the vector of parameters $\boldsymbol{\beta}$ that determine the conditional expectation functions we are attempting to estimate. The error term ε_i denotes a zero-mean symmetrically distributed random variable representing unobserved heterogeneity. For notational simplicity, we express the encompassing empirical models described above using an abuse of notation that re-uses Greek symbols that should in fact be distinct theoretical objects. We then further abuse notation by re-using Greek symbols in different model specifications with different dependent variables, different conditional mean specifications, and different assumptions about the distribution of the error, which we aim to make clear with the discussion of model specifications below.

All estimations presented in this dissertation are performed using STATA version 13.0.

4.1 Annual Expenditure at OFM

The first dependent variable we consider is *AnnualSpend*, which is estimated in log-form because of the skewness of its distribution seen earlier in Figure 1. The equation we estimate using OLS is:

$$LnAnnualSpend_i = \beta_0 + \boldsymbol{\beta X}_i + \varepsilon_i \, .$$

An endogeneity issue arises for the behavioural variables *Organic*, *FreeRange* and *DrinksOutdoor*, because these purchasing behaviours incur different expenditures, which is the dependent variable. To correct this endogeneity issue by which some right-hand-side variables are likely correlated with the error term, we present a two-stage least squares estimation instrumenting the endogenous variables with *Hour* and *Interviewer* fixed effects, based on the intuition that the spatial distribution of interviewers (e.g. randomly selected locations but with little within-interviewer variation, with some standing closer to organic providers and others farther away) provides information correlated with interest in particular product attributes but uncorrelated with spend. Assuming *Hour* and *Interviewer* fixed effects are correlated with the endogenous variables and unrelated to the error term ε_i, these variables should be suitable instrumental variables.[12] The following three equations for the endogenous variables are estimated by OLS:

$$Organic_i = \alpha_0 + \boldsymbol{\alpha}_1\boldsymbol{X}_i + \alpha_2 Hour_{ij} + \alpha_3 Interviewer_i + u_i \, ,$$

$$FreeRange_i = \pi_0 + \boldsymbol{\pi}_1\boldsymbol{X}_i + \pi_2 Hour_{ij} + \pi_3 Interviewer_i + v_i \, ,$$

$$DrinksEating_i = \rho_0 + \boldsymbol{\rho}_1\boldsymbol{X}_i + \rho_2 Hour_{ij} + \rho_3 Interviewer_i + w_i \, ,$$

where u_i, v_i and w_i are random error terms in the respective first-stage equations. The second stage is then estimated by OLS using predicted values from these three equations. Formally,

$$LnAnnualSpend_i = \beta_0 + \beta_1 \widehat{Organic_i} + \beta_2 \widehat{FreeRange_i} + \beta_3 \widehat{DrinksEating_i} + \boldsymbol{\beta}_{4K}\boldsymbol{X}_{4Ki} + \varepsilon_i \, ,$$

where $\boldsymbol{\beta}_{4K}$ and $\boldsymbol{X}_{4Ki}$ represent coefficients and regressors *other* than the three endogenous variables now notated explicitly in the equation above, and the overbar notation represents predicted values of regressors based on the first stage regressions.

[12] We assume there is information correlated between the instruments and the endogenous variables, though empirical correlations between *Organic* and the instruments are unfortunately weak.

4.2 Proportion of Household Food Expenditure Spent at OFM

The estimation of *PropAnnualSpend*$_i$, must account for the boundedness of the variable between zero and one:

$$0 \leq PropAnnualSpend_i \leq 1.$$

Of course OLS and general linear models may generate expected values outside the logically permissible range (Baum, 2008). Thus, our estimation follows the method by Parke and Wooldridge (1996) for regressions of fractional dependent variables estimated in STATA using the 'glm' command. To guarantee that all predicted values of *PropAnnualSpend* take on values strictly inside the unit interval (0,1), we assume, for all *i*, that:

$$E(PropAnnualSpend_i|\boldsymbol{X}_i) = \Phi(\boldsymbol{\beta X}_i),$$

where $\Phi(.)$ represents the standard normal cumulative probability density function (cdf) and $\boldsymbol{\beta}$ is a parameter vector conformable with $\boldsymbol{X}_i$. Heteroskedasticity is likely to be present in the specification above since the variance of *PropAnnualSpend* given $\boldsymbol{X}_i$ is unlikely to be constant when $0 \leq PropAnnualSpend_i \leq 1$. Our estimation therefore uses robust standard errors. We report average marginal effects, which is the average of the marginal effect for each observation.

4.3 Shopping Frequency at OFM

Given the dichotomous nature of the variable *Weekly*, a probit model is estimated using maximum likelihood to measure marginal effects of consumer characteristics on the probability of shopping every week at OFM. Following Wooldridge (2000), the probit model is set up as follows.

Suppose an underlying latent variable y^* gives the true but unobservable value to the individual of his or her net benefit from shopping weekly at OFM for individual *i* where

$$y_i^* = \beta_0 + \boldsymbol{\beta X}_i + \varepsilon_i \, .$$

We can only observe the binary choice *Weekly* made by each individual, which is equal to one if the individual shops at OFM every week or zero otherwise,

$$Weekly_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0. \end{cases}$$

Assuming ε_i is normally distributed, the probability that y_i^* will be positive such that $Weekly_i$ = 1 can be defined as:

$$P(Weekly_i = 1|\boldsymbol{X}_i) = P(y_i^* > 0|\boldsymbol{X}_i) = P[\varepsilon_i > -(\beta_0 + \boldsymbol{\beta X}_i)|\boldsymbol{X}_i]$$
$$= 1 - \Phi[-P[\varepsilon_i > -(\beta_0 + \boldsymbol{\beta X}_i)]$$
$$= \Phi(\beta_0 + \boldsymbol{\beta X}_i).$$

The marginal effect of a continuous independent variable x_j (from the vector $\boldsymbol{X}$) is derived from the partial derivative

$$\frac{\delta P(Weekly=1|\boldsymbol{X})}{\delta x_j} = \phi(\beta_0 + \boldsymbol{\beta X})\beta_j,$$

where $\phi(.)$ is the derivative of the normal cdf $\Phi(.)$ (i.e. $\phi(.)$ is the standard normal pdf). If $x_1$is a binary independent variable, the partial effect of changing from zero to one is

$$\Phi(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k) - \Phi(\beta_0 + \beta_2 x_2 + \cdots + \beta_k x_k),$$

where there are k independent variables included in the model. We report average marginal effects, which is the average of the marginal effect for each observation. Because the probit model is nonlinear, it is estimated using maximum likelihood estimation (MLE).

4.4 WTP for Local Production

We estimate the variables *DiscountChina* and *DiscountUSA*, which are the percentage discounts in an individual's WTP for a Chinese and US product, respectively, compared to a NZ grown (but otherwise identical) product, conditional on consumer characteristics. For these variables a Tobit model is necessary because of the clusters of observations at one, corresponding to consumers reporting a maximum discount (i.e. precisely zero WTP for the food product if it is from China or the U.S. but strictly positive WTP for the otherwise identical one produced in NZ). Following Wooldridge (2000), we estimate a Tobit model as follows. First we define a latent variable z_i^* which can be modelled in the classical linear form:

$$z_i^* = \beta_0 + \boldsymbol{\beta X_i} + \varepsilon_i,$$

$$DiscountChina_i = \min\{(\boldsymbol{\beta X_i} + \varepsilon_i), 1\}.$$

These definitions imply that the discount is equal to the latent variable z_i^* when $z_i^* < 1$ but is assigned a value of one otherwise.

We report the average marginal effects of x_j (an individual covariate within the vector $\boldsymbol{X}$) which is the derivative of $E(Discount_i|\boldsymbol{X})$, with respect to x_i. Wooldridge (2000) shows this is derived as:

$$\frac{\partial E(DiscountChina_i|\boldsymbol{X})}{\partial x_j} = \beta_j \Phi(\boldsymbol{\beta X}/\sigma).$$

We take the same steps to estimate a similar model replacing *DiscountChina* with *DiscountUSA*.

To estimate *DiscountNZnonlocal* we are able to use a simple OLS linear regression as there is no clustering in its distribution:

$$DiscountNZnonlocal_i = \beta_0 + \boldsymbol{\beta X}_i + \varepsilon_i.$$

4.5 Chow Test for Different Coefficients on $\boldsymbol{X}_i$

Out of interest for the divide in consumers who place a positive value on foreign products and those who do not, we test whether the conditional means of *WTPNZ* for consumers with *WTPChina*>0 is the same or different from the conditional mean of *WTPNZ* for consumers with *WTPChina*=0. We estimate the following OLS regression which effectively pools separate regressions for the two groups into a single estimation:

$$LnWTPNZ_i = \beta_0 + \gamma China\_Positive_i + \tau LnWTPChina_i + \boldsymbol{\beta X}_i +$$

$$\boldsymbol{\delta}(China\_Positive_i \times \boldsymbol{X}_i) + \varepsilon_i,$$

where □ is a parameter vector (the same size as $\boldsymbol{\beta}$) of coefficients on interaction terms. We use this encompassing specification to test whether interaction terms are jointly zero using a simple F-test. The null hypothesis in this case is:

$$H_0: \boldsymbol{\delta} = 0.$$

The alternative hypothesis is then:

$$H_1: \text{At least one of the coefficients in } \boldsymbol{\delta} \neq 0.$$

A rejection of the null hypothesis would suggest the two groups exhibit different coefficients (i.e. slopes) on each variable when regressed separately.

We run this same test for *LnWTPNZ* replacing *WTPChina* with *WTPUSA* and the dummy variable *China_Positive* with *USA_Positive* for comparison. We also employ a Chow Test of the same form to the model of *LnAnnualSpend* described in section 4.1 to check for differences in coefficients for on-site and online respondents. For this second Chow Test, we simply replace *WTPNZ* with *LnAnnualSpend* and *China_Positive* with Online in the above equation.

5 Results

Results are presented in three sections: customer shopping behaviour at OFM, WTP for local production, and robustness tests. We are interested in how inclusion of each group of variables affects the coefficient estimates, but primarily interested in the fully conditional models corresponding to final specification.

5.1 OFM Customer Shopping Behaviour Results

Table 9 shows the results of the OLS estimates of three empirical models of *LnAnnualSpend*. When only demographic variables are included on the right-hand side as in Model 1 in Table 9, age has one of the more noticeable effects: over-50 status is associated with an increase in expected annual spend that is 303% greater ($e^{1.394}$-1=3.03) than for an 18-to-29-year-old whose other characteristics are the same. This result is highly significant both in statistical and economic terms although its magnitude declines in Model 2 and is not significantly different from zero in Model 3. This instigates an interesting challenge for marketers of local food as to how best to use information about demographics combined with more detailed information about preferences. While it appears older people tend to do more shopping at OFM than younger people do, this pattern is largely explained by information about consumer preferences and the constraints they face (c.f. Szmigin, Maddock and Carrigan's 2003 paper arguing that 'sense of community' at farmers markets may be particularly appealing to older consumers).

The coefficient on *LnHhincome* provides an income elasticity measure, which is positive and significant at the one percent level across all columns. The third model predicts that a one percent increase in household income is associated with a 0.78% increase in annual spend. The magnitude of the income elasticity of OFM annual spend being less than unity is consistent with the idea that food is a necessity, as noted in Engel's law that households spend a smaller portion of their income on food as income increases (Calhoun, 2002). This contradicts views in the community that foods from OFM are 'luxury' items. There is no significant effect of the number of adults or presence of children in the household, which suggests having more people to feed is not a key driver of expenditure at OFM, nor does being busy with children on Saturday mornings significantly constrain it. Also seen in Table 9, living outside of Dunedin has a large, negative effect on expected annual spend in all models, just as one would expect since people living farther away are, all else equal, less likely to visit OFM as frequently.

Expressing a preference for *FreeRange* food is expected to increase annual spend in Model 2 by 139% ($e^{0.872}$-1 = 1.392) but appears to be explained away with the addition of attitudinal

Table 9: OLS Estimates of Three Emprical Models of LnAnnualSpend			
	(1)	(2)	(3)
Variables	Demographics	+ Behaviours	+ Attitudes
Age = 30 to 49	0.535	0.658	0.0911
	(0.457)	(0.412)	(0.441)
Age = 50+	1.394***	1.212***	0.181
	(0.427)	(0.388)	(0.427)
Male	-0.262	-0.244	-0.112
	(0.314)	(0.286)	(0.302)
University	0.113	-0.173	0.156
	(0.355)	(0.317)	(0.343)
LnHhIncome	0.718***	0.601***	0.781***
	(0.220)	(0.198)	(0.224)
Adults = 2	0.149	0.206	0.101
	(0.370)	(0.324)	(0.348)
Adults = 3+	0.225	0.407	0.597
	(0.418)	(0.369)	(0.379)
Children	-0.286	-0.361	-0.453
	(0.455)	(0.407)	(0.417)
OutsideDunedin	-1.860***	-1.814***	-1.975***
	(0.487)	(0.427)	(0.495)
FreeRange		0.872***	0.427
		(0.293)	(0.321)
Organic		0.197	0.446
		(0.303)	(0.327)
DrinksEating		-0.330	-0.866***
		(0.295)	(0.325)
LocalOther		0.334	0.242
		(0.319)	(0.336)
Service			0.701*
			(0.371)
Quality			0.359
			(0.329)
Fresh			0.109
			(0.308)
Local			0.185
			(0.333)
Atmosphere			-0.0621
			(0.348)
Prices			-0.687*
			(0.409)
Time			-1.019**
			(0.390)
Weather			-0.551*
			(0.317)
Money			-0.190
			(0.539)
Constant	-1.933	-1.251	-2.276
	(2.138)	(1.942)	(2.159)
Interviewer Fixed Effects	no	no	no
P-value for null of Demographic variables jointly zero	0.0000***	0.0000***	0.0003***
P-value for null of Behavioural variables jointly zero		0.0059***	0.0041***
P-value for null of Attitudes variables jointly zero			0.0366**
Observations	113	111	96
R-squared	0.381	0.512	0.605
Adjusted R-squared	0.3268	0.4465	0.4853

Standard errors appear in parentheses
*** p<0.01, ** p<0.05, * p<0.1

controls. A preference for *Organic* food is not shown in any model in Table 9 to significantly affect *AnnualSpend*. However, in column (3), the drinks and food variable is associated with expected annual spend that is 58% less than for those who visit without staying onsite to eat and drink ($e^{-0.866}$ -1= -0.579). Appendix 2 provides further results using the same model specifications but for the dependent variable *Spend* (on the day of the survey rather than imputed *AnnualSpend*). The results in the Appendix and subsequently reported marginal effects in a Probit model of *Weekly* suggest that *DrinksEating* is a predictor of fewer shopping days per year as well as a negative impact on expected spend on a given shopping trip (expected *Spend* is $16 lower if one buys pre-prepared food or drink, all else equal, in which case one is also 20% less likely to shop every week at OFM, all else equal).

Choosing to shop at OFM because of the 'good' *Service* from vendors (and ability to interact with producers) is associated with around a double in *AnnualSpend* ($e^{0.701}$-1 =1.016 or a 102% increase). People who enjoy the *Service* at the market may particularly look for a relationship with the seller or producer which supermarkets tend not to provide. This would confirm some consumers may be seeking self-actualisation which Westervelt and Hawkins were not able to find in 1979. Shopping frequency is the more important channel through which perceived advantages of OFM vendors' superior service affects *AnnualSpend*. This is shown in that *Service* is significantly positive in regressions of *Weekly* (see marginal effects reported below) though not with Spend (see Appendix 2). Preference for OFM prices, and mentioning *Time* and *Weather* as barriers to spending more at OFM are all negatively associated with *AnnualSpend*, as per intuition. *Time* has a particularly large effect, reducing expected *AnnualSpend* by 64% ($e^{-1.019}$ - 1 = -0.639).

Turning now to the joint tests whose associated p-values are reported at the bottom of Table 9, we see the sets of demographic, behavioural and attitude variables are all jointly significant across all models in which they are included at least at the five percent level. Goodness of fit is fairly high across all models but especially in the third model with R-squared values of 57% of variance explained. While this could be high due to the large number of variables included, adjusted R-squared is also considerably high with 44% of variance explained in Model 3.

We continue investigating characteristics associated with *AnnualSpend* by shifting focus to a fractional Probit model of *PropAnnualSpend* and its average marginal effects as presented in Table 10, which are relevant to a base rate of 21%. Consistent with the *LnAnnualSpend* models in the previous table, noteworthy marginal effects in Table 10 include the positive effect of

Table 10: Fractional Probit Average Marginal Effects of Three Empirical Models of PropAnnualSpend

Variables	(1) Demographics	(2) + Behaviours	(3) + Attidues
Age = 30 to 49	0.0502	0.0407	-0.0185
	(0.0489)	(0.0522)	(0.0613)
Age = 50+	0.134**	0.107*	-0.0194
	(0.0537)	(0.0555)	(0.0599)
Male	-0.0223	-0.0257	-0.000680
	(0.0410)	(0.0398)	(0.0452)
University	0.0337	0.0201	0.0401
	(0.0437)	(0.0419)	(0.0523)
LnHhIncome	0.0251	0.00929	0.0390
	(0.0261)	(0.0271)	(0.0312)
Adults = 2	0.00514	0.00686	0.0196
	(0.0483)	(0.0459)	(0.0492)
Adults = 3+	-0.0308	-0.0147	0.00573
	(0.0508)	(0.0518)	(0.0516)
Children	-0.0655	-0.0477	-0.0992**
	(0.0490)	(0.0460)	(0.0434)
OutsideDunedin	-0.166***	-0.156***	-0.198***
	(0.0334)	(0.0352)	(0.0279)
FreeRange		0.0444	-0.0196
		(0.0414)	(0.0493)
Organic		-0.00875	0.0405
		(0.0401)	(0.0459)
DrinksEating		-0.0875**	-0.146***
		(0.0386)	(0.0339)
LocalOther		0.0807*	0.0667
		(0.0463)	(0.0453)
Service			0.128**
			(0.0647)
Quality			0.0287
			(0.0480)
Fresh			0.0336
			(0.0438)
Local			0.106***
			(0.0395)
Atmosphere			0.0501
			(0.0489)
Prices			-0.00707
			(0.0554)
Time			-0.129***
			(0.0433)
Weather			-0.0687
			(0.0495)
Money			-0.0496
			(0.0719)
Interviewer Fixed Effects	no	no	no
P-value for null of Demographic variables jointly zero	0.0000***	0.0022***	0.0000***
P-value for null of Behavioural variables jointly zero		0.0246**	0.0003***
P-value for null of Attitudes variables jointly zero			0.0001***
Observations	106	104	90

Standard errors appear in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors are used

over-50 status in Model 1 (with disappearing significance as more conditioning information is included. A preference for *Service* again has a significantly positive effect, and, as in the previous model, being from outside Dunedin or purchasing ready-to-eat food or drinks have significantly negative effects (e.g. in Model 3 in Table 10, *DrinksEating* reduces the expected proportion of spend at OFM by 15 percentage points which is rather large compared to the 21% base rate). *Time* as a barrier again translates to a negative effect as one would expect, reducing the expected proportion by 13 percentage points.

In contrast to the models of *AnnualSpend* considered in the previous table, *PropAnnualSpend* is lowered by close to 10 percentage points by having children in Model 3 and is not responsive to income (likely because the model effectively holds constant the household total food budget). Somewhat surprisingly in Table 10, there is no effect of *FreeRange* (which did significantly increase expected annual spend) or *Organic*. Shopping at OFM for the reason that its products are locally produced raises expected proportion spent at OFM by a significant 11 percentage points in the final column of Table 10. This implies, given OFM shoppers with a strong preference for local food were not predicted to spend more on food at OFM in Table 9, they are likely to spend less on food elsewhere. Unlike the previous estimation, there is no significant effect of *Prices* or *Weather* in Table 10.

Joint significance tests reported at the bottom of Table 10 show all groups of variables are statistically significant in specifications in which they appear, at least at the five percent level. Tests of the null hypotheses that different groups of variables have jointly zero effect on the probability of being weekly are mostly rejected at high levels of statistical significance.

Table 11 shows the average marginal effects obtained from the Probit model of the probability that an individual is a weekly shopper conditional on the same set of right-hand side variables as in the models of expenditure reported above. These results show no association between *Age* and the probability of being a weekly shopper until, surprisingly, when adding in attitudinal variables the association becomes significantly negative (this is the direct opposite of how age affected *LnAnnualSpend* and *PropAnnualSpend*). This could possibly reflect an increased opportunity cost of time for older persons after controlling for all other variables. However, this does not align with most other findings in the literature in which age has had a positive or

Table 11: Average Marginal Effects of Three Emprical Models of Weekly

Variables	(1) Demographics	(2) + Behaviours	(3) + Attitudes
Age = 30 to 49	-0.235	-0.0750	-0.155
	(0.382)	(0.115)	(0.102)
Age = 50+	0.186	0.0229	-0.197**
	(0.358)	(0.111)	(0.0899)
Male	0.174	0.0576	0.0530
	(0.275)	(0.0844)	(0.0863)
University	0.157	0.0302	0.0425
	(0.303)	(0.0963)	(0.108)
LnHhIncome	0.697***	0.202***	0.199***
	(0.197)	(0.0514)	(0.0522)
Adults = 2	-0.0575	-0.0221	0.133
	(0.318)	(0.0959)	(0.100)
Adults = 3+	-0.0130	-0.00786	0.0576
	(0.357)	(0.108)	(0.100)
Children	-0.674*	-0.170	-0.253**
	(0.406)	(0.116)	(0.111)
OutsideDunedin	-1.718***	-0.475***	-0.440***
	(0.597)	(0.0883)	(0.117)
FreeRange		0.189**	0.0900
		(0.0910)	(0.0910)
Organic		-0.0455	0.0110
		(0.0866)	(0.0953)
DrinksEating		-0.232***	-0.202**
		(0.0874)	(0.0946)
LocalOther		-0.0847	-0.0483
		(0.0913)	(0.0913)
Service			0.250**
			(0.109)
Quality			0.197**
			(0.0890)
Fresh			0.0861
			(0.0909)
Local			0.220**
			(0.104)
Atmosphere			0.115
			(0.0868)
Prices			-0.0726
			(0.108)
Time			-0.296***
			(0.0917)
Weather			-0.223***
			(0.0860)
Money			-0.107
			(0.140)
Interviewer Fixed Effects	no	no	no
P-value for null of Demographic variables jointly zero	0.0073***	0.0000***	0.0000***
P-value for null of Behavioural variables jointly zero		0.0075***	0.1046
P-value for null of Attitudes variables jointly zero			0.0000***
Observations	116	114	98
Pseudo R-Squared	0.1939	0.2734	0.4368

Standard errors appear in parentheses
*** p<0.01, ** p<0.05, * p<0.1

no effect on intensity of local food shopping. The association between household income and the probability of being a weekly shopper, which is a large-magnitude effect of a 20 percentage point increase relative to the unconditional rate of 51% (i.e. a 39% relative increase) associated with a doubling of household income in the final specification. Having children reduces the expected probability of shopping weekly at OFM, with a 25 percentage point decrease in Model 3 of Table 11, likely reflecting less flexibility in shopping hours for parents, especially on Saturday mornings, when it is common for NZ children to participate in sporting or other activities.

As discussed earlier, respondents who say they come to OFM to purchase drinks and prepared food are far less likely to be weekly shoppers. Those who mentioned *Service* or *Quality* as a main reason for shopping at the market were 25 and 20 percentage points, respectively, more likely to be weekly shoppers. A preference for quality has been frequently noted as an influential factor on local food shopping behaviour in the literature but 'good service' (i.e. friendly vendors and the opportunity to interact with them) has been less prevailing. In our own data *Service* seems to be a particular motivator for OFM customer loyalty, in fact it has significant and positive effects in all three sets of empirical results presented thus far. We also note the relatively large positive associations between favour for *Local* products and being a weekly shopper, which has no significant effect in the *AnnualSpend* estimations.

As in the expenditure models, the main barriers negatively associated with the probability of being a weekly shopper are unsurprising. According to Table 11, limited hours of operation (coded by the variable *Time*) and 'bad' *Weather*, when mentioned as barriers to spending more at OFM, are associated with a 30 and 22 percentage point reduction in the likelihood of being a weekly shopper, respectively.

Variables within each grouping are jointly significant at the one percent level of confidence in all cases except for behavioural variables in Model 3 of Table 11.

5.2 Local Production Premium Results

Table 12 presents average marginal effects from the Tobit model of *DiscountUSA*, interpreted as the consumer's subjective percentage discount applied to value of a U.S.-produced food item over an otherwise similar NZ item. Results of a similar model for *DiscountChina* are presented in Appendix 3 but could not be estimated for the full specification.

Table 12: Average Marginal Effects of Three Tobit Models of DiscountUSA

Variables	(1) Demographics	(2) + Behaviours	(3) + Attitudes
Age = 30 to 49	0.615***	0.526***	0.319***
	(0.167)	(0.167)	(0.105)
Age = 50+	0.665***	0.534***	0.178
	(0.155)	(0.171)	(0.164)
Male	-0.228*	-0.181	-0.0136
	(0.121)	(0.117)	(0.0761)
University	-0.0797	-0.133	-0.242**
	(0.107)	(0.126)	(0.109)
LnHhIncome	0.115	0.157**	0.261***
	(0.0707)	(0.0735)	(0.0557)
Adults = 2	-0.310**	-0.328**	-0.302**
	(0.140)	(0.137)	(0.119)
Adults = 3+	-0.0414	-0.0363	0.0319
	(0.119)	(0.116)	(0.0738)
Children	0.238*	0.209	0.148
	(0.133)	(0.139)	(0.155)
OutsideDunedin	-1.136*	-0.813	-0.898**
	(0.633)	(0.607)	(0.444)
FreeRange		0.0536	-0.0996
		(0.136)	(0.120)
Organic		0.174	0.386***
		(0.132)	(0.116)
DrinksEating		-0.0725	-0.399***
		(0.131)	(0.146)
LocalOther		-0.105	-0.167**
		(0.111)	(0.0760)
Service			-0.341**
			(0.152)
Quality			-0.0174
			(0.126)
Fresh			0.0465
			(0.101)
Local			0.674***
			(0.148)
Atmosphere			0.381***
			(0.0995)
Prices			-0.0444
			(0.105)
Time			-0.245**
			(0.107)
Weather			-0.0876
			(0.0972)
Money			0.0806
			(0.128)
P-value for null of Demographic variables jointly zero	0.0000***	0.0000***	0.0000***
P-value for null of Behavioural variables jointly zero		0.4249	0.0001***
P-value for null of Attitudes variables jointly zero			0.0000***
Observations	51	50	48
Number of censored observations	26	25	25
Psuedo R-squared	0.3611	0.394	0.8003

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results in Table 12 suggest that consumers over the age of 29 are likely to discount U.S. produced food more than younger people interviewed at OFM, though significance for the 'over 50' category fades in Model 3, quite consistent with models of OFM shopping behaviour. Quite surprisingly in Table 12, individuals with higher education appear to expect a 24 percentage point smaller discount, controlling for all other characteristics, compared to a base rate of 56%. A doubling of household income is expected to be associated with a 26 percentage point higher discount in WTP which is intuitive that higher income earners can afford to pay a higher premium for particular preferences. Living in a household with two members has a large and significant negative effect on the discount compared to having only one household member. Being from outside of Dunedin is, in our data, negatively associated with WTP a domestic-food premium (which might make sense if these shoppers are primarily attracted to OFM as a tourism activity in Dunedin rather than an interest in local food per se).

We also see positive associations with *Organic* and negative with *DrinksEating*, as well as, quite surprisingly, *LocalOther* and *Service.* These negative effects may be counteracted by a much larger positive effect of shopping at the market because the produce is *Local*, which implies a much higher (67 percentage point) discount, and the positive effect of *Atmosphere* (of 38 percentage points). *Time* has a negative effect suggesting people who are 'busier' (at least on Saturday mornings) have less interest in paying for local production. The three variable groups each have some statistical significance jointly in almost all of the model specifications.

While we cannot compare results across the fully specified models of *DiscountUSA* and *DiscountChina* (in Appendix 3), we conclude that while people overall value US produce slightly higher than Chinese produce (as reported in Section 3), there is no particular individual characteristic which responds particularly differently to the foreign country of origin.

Not surprisingly results for the OLS estimates of determinants of the WTP a premium for Otago over non-Otago NZ produce returned few significant results (see Appendix 4 for results table). Main results included a (surprisingly) negative effect of *FreeRange*, negative effect of *DrinksEating*, and positive effect of *Atmosphere*. With such a small average premium reported and little variance little significance was to be expected.

Results of the model of *LnWTPNZ* conditional on *WTPChina* are reported in Appendix 5 and similarly for *WTPUSA* in Appendix 6.[13] The set up of this model allows a Chow Test to be

[13] In the implementation of this model we find some issues with collinearity due to small numbers of observations meaning not all terms could be included. Ideally with a larger sample size we could test across a full set of interaction terms, but following a long tradition in statistics suggesting that cells in any design matrix

performed to check the equality of coefficients across the group of customers willing and that unwilling to buy the foreign (Chinese or US) product. P-values of the Chow Test reported at the bottom of Appendices 5 and 6 show coefficients common to the two groups are statistically different at the five percent level in Model 1 but significance fades with the addition of more conditional information. As a result we are unable to conclude with certainty whether variables that affect individuals' WTP for the NZ grown product do so in different ways, depending on whether the individual is willing or not to buy the foreign version. The fact that in the full specification we cannot reject the hypothesis that the coefficients are equal across the two consumer types for either dependent variable is possibly a parsimony issue since there are such a large number of parameters to be estimated. However, we cannot rule out that coefficients are no different across the two groups in the fully specified model.

In the first specification (i.e. with the least variables included), results show the group with positive WTP for the US good are expected to pay a premium of around 15% over the maximum price they are willing to pay for the NZ product, given the responses to other variables are held fixed. Compared to the Chinese good, the conditional premium for local production is five percent. These are both much smaller than the unconditional premiums estimated in Section 3.1, and reduce further in magnitude and statistical significance as more dependent variables are added to the models.

5.3 Robustness Tests

A robustness check for possible interviewer effects is undertaken by including *Interviewer* fixed effects and *Hour* in the models of *LnAnnualSpend* (see Appendix 7). We are assured that interviewer effects are not jointly significant at the five percent level and results are fairly consistent with the original estimations. In some specifications, *Hour* has a strongly negative effect on annual spend implying that being interviewed one hour later decreases expected annual spend at OFM by 26% in Model 3 of Table 18 ($e^{-0.302}-1 = -0.261$). It could be that high spenders are temporally concentrated in the early hours of operation with lower-spending shoppers arriving later.

with fewer than five observations should be dropped. We also tried this test with the full set of interactions by accepting our software's (STATA 13) automated dropping due to collinearity and reach the same decisions on the null hypothesis.

A Chow Test for differences in coefficients of on-site and online respondents reported in Appendix 8 rejects the null hypothesis at the five percent level in all 3 specifications.[14] Thus, we find little evidence in the data pointing to bias from interviewer effects or the online survey.[15]

Appendix 9 shows the 2SLS approach of the *LnAnnualSpend* estimation (described in section 4.1) is somewhat altered from OLS estimation. The significance of *FreeRange* is lost in Model 2 while the effect of *DrinksEating* becomes stronger in magnitude in Model 3. This would suggest that a preference for *FreeRange* products does not have a significant effect on yearly spend at OFM when taking out the cost of such products, whereas a preference for ready-to-eat food and drinks has a stronger effect on spending when you take away the effect of prices of these items. Effects of other variables are only slightly effected, except that *Service* loses its significance and *Quality* becomes a newly, though weakly, significant variable.

One might reasonably raise concerns about the possibility that *WTPChina*>0 or *WTPUSA*>0 status is endogenous in the models of *LnWTPNZ*. We therefore ran an endogenous treatment effect model as laid out by Cong and Drukker (2000), using STATA's 'etregress' command.[16] The results for the model conditional on *WTPChina*, reported in Appendix 10, predict a treatment effect of positive WTP for the Chinese product reduces *WTPNZ* buy $8.80. However, we found our small sample size to be an issue in the ability of STATA to estimate this model, and were unable to include all desired independent variables at once. Results are highly sensitive to the variables which were included, where some show the treatment effect is not significantly different from zero.

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[14] Following the same issue of collinearity in the Chow Test presented in section 5.2, we dropped cells with fewer than five observations. Results for the Chow test are robust across this method and allowing automatic dropping of variables due to collinearity by STATA.

[15] We only report robustness tests for the main model of *LnAnnualSpend*. To check on robustness with respect to inclusion of interviewer fixed effects we re-ran all models that we could with interviewer fixed effects (with 5 or more observations per interviewer), finding evidence to reject the null of no joint effect only in the *PropAnnualSpend* variable and, even there, with sensitivities that make joint significance easily disappear. The interpretation we attach to all runs of models with interviewer fixed effects is that there does not appear to be serious problems with particular interviewers eliciting unusually large or small values for the variables analysed in this study.

[16] For this a linear regression model of *WTPNZ* conditional on the WTP for the foreign item and the main independent variables of interest is augmented with an endogenous binary treatment variable, where the decision to buy the foreign product is set as the outcome of an unobserved latent variable. We assume the latent variable is a linear function of the main independent variables.

6 Discussion

The characteristic which most consistently influences shopping behaviours at OFM is household income, which appears to positively affect shopping at OFM across all dimensions explored, even shopping frequency. This signals opportunities for OFM or surrounding local food developments to attract and cater more to lower income earners. A preference for 'good service' (i.e. 'friendly' vendors and the possibility to 'interact' with them) is also positively associated with all main OFM shopping behaviours which we model. This is strong evidence that OFM is particularly attractive to those looking for a more personal shopping experience and the chance to connect with the producers of the food they buy, which new local food developments may want to consider.

Comparisons across sets of results prompt further inferences about OFM customers, though the following conclusions we draw should not be taken as concrete given the models contain different sample sizes. Consumer characteristics which are expected to increase both annual spend at OFM and WTP for local production include being over 50 years old and having higher household income (in most cases). This implies customers with such characteristics place higher utility on local production as an attribute of food, and consistent with this, spend relatively more on local food products at OFM. Similarly, having not purchased ready-to-eat food or drinks and being from outside Dunedin are expected to decrease both annual spend at OFM and WTP for local production. Intuitively this makes sense considering customers at OFM to buy prepared food and drinks or visiting from out of town are likely at OFM to enjoy outdoor eating or observe local culture than specifically to find local food.

Several variables are seen to have significant effects in models of WTP for local production but not in those of OFM expenditure. Namely, these are: being aged 30 to 49 (compared to a reference category of 18 to 29 year olds); having a preference for organic foods at OFM; and shopping at OFM because the products are local or because of its atmosphere. It appears that these characteristics are associated with an increased value for local production but this does not translate into higher spending at OFM. We do not have enough information to conclude whether this indicates a gap between intentions described by respondents and behaviours reported (consistent with theory in Young, DeSarbo and Morwitz (1998)), or if they are more likely than others to find other sources of local food, such as having their own garden.

Our results also suggest that shopping at OFM because the products are local is expected to increase the proportion of total food purchases carried out at OFM by 11 percentage points.

This would suggest that, although individuals with this characteristic do not spend significantly more in a year at OFM than others, their spending at OFM does tend to make up more of their total food spending. This could mean they spend less overall on food by choosing cheaper products (which would be in line with the study we reviewed by Mirosa and Lawson (2012) which finds local food consumption is associated with frugality), wasting less food or growing and foraging one's own food.

From this same comparison of models, we are encouraged to see that weather as a barrier is negatively associated with expenditure at OFM but not significant in models of WTP for local production.[17] This implies potential changes for OFM to attract revenue from customers who are likely interested in their products but perceive the indoor location to be a significant deterrent to shopping there. However, time as a barrier is negatively associated with both expenditure at OFM and WTP for local production.

Overall, our results are relatively robust to the inclusion of interviewer fixed effects and for comparisons between respondents recruited to do onsite interviews and online surveys. However, we do want to acknowledge several limitations of our data that imply caution is warranted in how reliably results reported in this study can be generalised. Small sample sizes of course limit the precision with which conditional expectations, even if correctly specified, can be estimated. This problem also resulted in the inability of STATA to estimate some of our models with large numbers of independent variables.

Selection bias is a potential issue in our data, which we think does an admirable job of avoiding. OFM organisers do a count every March of the number of customers coming through the market gates. For the past two years this number has been approximately 7,500 customers (email sent to authors by Vercoe, July 22, 2015). Therefore, our sample size of 137 covers around 2.1% of the estimated population of shoppers. We believe we made every intention to draw a representative sample from that population. We tried to spread interviewers both temporally and spatially when conducting survey interviews to avoid introducing obvious systematic selection (e.g. shoppers who tend to shop at a particular time period or are fans of one particular stall). Nevertheless, the data is potentially affected by selection effects, regarding especially the degrees to which potential respondents were time constrained when approached by our team of interviewers.

[17] This comparison is based off results from *DiscountUSA* as it could not be estimated for *DiscountChina*.

7 Conclusion

We learn a great deal about OFM consumers' preferences in this study from empirical analyses of annual spend, frequency of shopping, and proportion of total food spending carried out at OFM. Characteristics which most consistently have positive influences across these shopping behaviour dimensions are household income and a preference for 'good service' of vendors at OFM. The income elasticity measure we estimate, conditional on all other dependent variables, predicts that a one percent increase in household income is associated with a 0.78% increase in annual spend.

Several variables in models of OFM shopping behaviour have consistently negative effects. These variables include: living in an area outside of the city where the OFM is held; having mentioned time as a barrier to spending more at OFM; and shopping at OFM for drinks or ready-to-eat food. Our descriptive analysis shows there is an inexplicit divide across consumers - most frequent shoppers tend to come mainly for groceries, while those who do not attend every week are more inclined to enjoy the market's café culture. The time barrier variable has a negative effect on spend in a single visit at OFM, suggesting it is more than just an obstacle to getting to the market.

Among other interesting findings, our data reveal the effects of shopping at OFM for free range or organic foods is not as strong as theory would anticipate, with few significant effects across models. Shopping at OFM because of its 'good service' and quality products are the main attitudes of customers which increase yearly spend. These effects are channelled from more frequent visits to OFM, rather than spending more in a single visit.

In addition to analysis of OFM shopping behaviour, this project fosters understandings of how OFM customers value local production, based on information of consumer WTP for food products that are from different locations but are otherwise equivalent. We find that, on average, customers are willing to pay 62% less for Chinese produce (and 56% less for US produce) than NZ produce. In contrast, the consumers are only willing to pay five percent less for produce grown somewhere in NZ than for produce specifically from the local region. From another point of view, we find the premium customers are willing to pay for Otago-produced food over NZ produce ranges between at least 2.1% and eight percent. Upon further inspection of the data we uncover two distinct groups of consumers with respect to the measures of WTP comparing NZ and foreign items - one is willing to buy both NZ and foreign produce items, and one is willing only to buy domestic produce but strongly opposed to purchasing the imported versions. This suggests that, although farmers markets are known to be highly attractive to consumers with strong preferences for local food, we still find a significant amount of OFM customers place positive value on some foreign food items. Testing for differences in how variables affect these two consumer groups' WTP for a NZ food product, we find there is likely no difference. However, this result was sensitive to model specification, and has a potential parsimony issue increasing the likelihood of drawing this conclusion.

We find the influence of many consumer characteristics on WTP for local production are largely in line with our findings on OFM shopping behaviour. However, customers who shop at OFM because the produce is locally produced, or because of the atmosphere of the market, or for organic foods, are more likely to pay a higher premium for local production, despite these having no effect on annual spending at OFM. Furthermore, while perceiving time and weather as barriers to spending more at OFM are significantly negatively associated with yearly spend at OFM, they do not appear to be related to customer WTP for local production.

We believe differences among particular subsets of consumers at OFM exposed by our research warrant further investigation. Future work could explore why some consumers are willing to buy foreign produce and others place flatly zero value on such items, and what individual characteristics influence whether OFM consumers primarily visit to shop for groceries or to enjoy drinks and prepared foods. It would also be valuable to apply similar methods to ours to a more representative group of food consumers in society, not just limited to OFM customers. In addition, considering consumer characteristics such as interest in health and nutrition, food and cooking, and environmental protection not represented in our data would be worthwhile.

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8 Appendices

Appendix 1: Otago Farmers Market Customer Survey

	Otago Farmers Market Customer Survey (1) **Date:** 28/03/2015 **Time:** ◻ 7am ◻ 7.30am ◻ 8am ◻ 8.30am ◻ 9am ◻ 9.30am ◻ 10am ◻ 10.30am ◻ 11am ◻ 11.30am ◻ 12pm **Location:** Otago Farmers Market **Interviewer:** __________	
	Hi I'm conducting a survey to find out what food issues are important to all of us who shop at Otago Farmers Market. Do you have some time to share your thoughts with us? First I need to you to take a look at the information sheet and sign that you give consent to participate in the survey.	
1	*For how many years have you been coming to the farmers market?*	Years:
2	*(If not first time) how frequently do you shop at the farmers market? E.g. one week in a month?*	
3	*Do your food shopping habbits change with the seasons?*	◻ No impact, I buy whatever I need. ◻ I want to buy seasonal but occasionally buy things out of season. ◻ I only buy what is in season
4	*Do you visit the farmers market to buy foods which are:*	◻ Organic or spray-free ◻ Fair trade ◻ Forest-stewardship ◻ Free-range
5	*Do you get food from anywhere other than the farmers market and retail stores? E.g.do you grow your own food?*	◻ I have my own garden and grow my own food ◻ Farm gate food vendors ◻ Food box / co-op initiatives ◻ Other:
6	*What is your favourite thing about the farmers market. Please explain:*	◻ Buying local is important to me ◻ The atmosphere/socialising ◻ The variety/specific selection of foods ◻ The prices of food items ◻ Other ____________________
7	*Have you already shopped or are you about to shop at the farmers market today?*	◻ Already Shopped ◻ About to shop ◻ Part way through
8	*How many stalls have you bought from or do you plan to buy from today?*	
9	*What products do you plan to buy or have you bought already at the farmers market today?*	◻ Fruit and/or vegetables ◻ Meat and/or fish ◻ Dairy products such as cheese ◻ Bottled beverages and/or condiments such as chutneys ◻ Pre-prepared foods and/or baking ◻ Drinks such as coffee and/or outdoor eating ◻ Non-food items or products such as cosmetics or plants ◻ Other ____________________
10	*How much do you plan to spend or how much have you spent already today at the farmers market?*	
11	*How much do you plan to spend or how much have you spent already on food at the farmers market today?*	
12	*How much does the household you are shopping for generally spend on food in a week, including farmers markets, grocery store spending, and restaurants?*	

	I now have some questions about you and your household which will help us to understand Farmers Market customers. We will not record any personal details that will enable you to be identified from your answers later	
13	*Could you tell me your age?*	
14	*Would you describe your gender as male or female?*	□ Male □ Female
15	*How would you describe your ethnicity or ethnic group?*	□ New Zealand European □ Other ____________________
16	*Where do you live?*	□ Dunedin □ Within Otago but outside of Dunedin □ Outside of New Zealand □ Outside of New Zealand
17	*Which transport did you use to get to the market today? E.g. walk, car, bike*	
18	*Using that transport, roughly how many minutes would you estimate that it took you to get to the market?*	Minutes:
19	*What is the highest level of formal education you have completed?*	□ Some high school but didn't complete □ Completed high school □ Completed polytechnic program □ Attended university but did not complete □ Graduated from university □ Post-graduate program completed
20	*Are you currently a student?*	□ Yes □ No
21	*What is your total annual household income before tax?*	$ ____________ □ Less than $25,000 □ $25,000 - $50,000 □ $51,000 - $75,000 □ $76,000 - $100,000 □ $76,000 - $100,000 □ $101,000 - $125,000 □ $126,000 - $150,000 □ Over $150,000
22	*The household you are shopping for includes how many people of each of the following age groups? Please include yourself in this answer.*	0-1 years of age:______ babies 1-12 years of age: _______children 13-17 years: _______ teens 18-25 years: _________ adults 26-65 years: __________ adults 66+ years: _________adults
23	*Do you have experience working as a farmer?*	□ Yes □ No
24	*Did anyone in your family have experience working as a farmer?*	□ Yes □ No
	I now have some questions about what you dislike about the market	
25	*I'd like you to think of a time when you wanted to shop at the farmers market but wound up not shopping there. What is the biggest barrier keeping you from spending more money at the farmers market? Please explain.*	□ Inconvenience □ Put off by the weather □ Prices □ Other ______________________
26	*What change would most increase how much you spend at the farmers market?*	
27	*What food items would you like to buy at the farmers market that you have not seen available there?*	

28	*Aside from the farmers market, can you name any retail stores where you regularly shop for food?* *E.g. Countdown*	□ Countdown □ New World □ Pak N Save □ Four Square □ Veggie Boys □ online □ Taste Nature □ Other ______________________
29	*When you shop at the farmers market, do you do any shopping at other stores on the same shopping run?*	□ Yes – how much do you normally spend? $ _______ □ No
	I now have some questions about how much you pay for different products.	
	Please think of a food item that you buy both at the farmers market and at a grocery store with same quality.	
30	*What item did you think of?*	____________________
	What price would you typically pay for the item at the farmers market?	$_________ per _______
	What price would you typically pay for the similar item if you weren't shopping at the farmers market?	$_________ per _______
	(Skip if haven't shopped yet) Can you think of a produce item that you bought at the farmers market today?	
31	*If price 10% less , buy the same amount or more?*	□ Same amount □ More % ____ more
	If price 50% less , would you buy same amount or more?	□ Same amount □ More % ____ more
	If price 10% more , would you buy same amount, or less?	□ Same amount □ Less % ____ less
	If price 50% more , would youbuy same amount, or less?	□ Same amount □ Less % ____ less
32	*Would you ever buy fresh salmon?* *(If no, prawns? Monk fish? - circle which used)* *In a typical instance of shopping for this item...*	
	...how much would you be willing to pay /kg for it?	$ ______ /kg
	Assuming all other quality aspects are the same *...how much would you be willing to pay for this item the if you were told the only option available was caught in NZ ?*	$ ______ /kg
	...China?	$ ______ /kg
	...Australia?	$ ______ /kg
	...Otago?	$ ______ /kg
33	*Would you ever buy lemons?* *(if no, oranges? Garlic? Tomatoes? - circle which used)* *In a typical instance of shopping for this item...*	
	... how much would you be willing to pay /kg for them?	**$ ______ /kg**
	Assuming all other quality aspects are the same... *...How much would you be willing to pay for this item if you were told the only option available produced in NZ ?*	$ ______ /kg
	...China?	$ ______ /kg
	...USA?	$ ______ /kg
	...Otago?	$ ______ /kg
34	*From product selected in above question... When buying _________, you see you have the option of New Zealand or USA _______. If they were both $_____/kg (PRICE THEY WERE WILLING TO PAY), which of the two would you buy?*	□ USA □ NZ
	If answer is NZ: *If NZ lemons stayed at that same price, what price would the USA product have to be for you to choose them over the NZ product?*	$ _________ /kg

35	*What was the last produce item you bought at a grocery store?*	____________________
	How much did you pay for it?	$ ______ per ______
	Was it a product of New Zealand?	◻ Yes ◻ No
	If yes , then what price would you have been willing to pay if it weren't a NZ product, assuming all other quality characteristics were the same?	$ ______ per ______
	If no , then what price would you have been willing to pay if it were a NZ product, assuming all other quality characteristics were the same?	$ ______ per ______
	I now have a few open-ended questions to finish with.	
36	*Name up to three reasons why you buy food at the farmers market:*	
37	*Do you consider yourself to be of Maori descent?*	◻ Yes ◻ No
38	*If yes , please describe what role Maori identity plays in how you view the costs and potential benefits of farmers markets and local food economies?*	
39	*What areas of improvement, if any, do you think could be implemented in the farmers market?*	
40	*Are there any other local food initiatives you think would make a positive impact in Otago moving forwards?*	
41	*How would you summarise your overall experience at the farmers market?*	
42	*Do you have any other comments or questions?*	
	That is the end of the survey. Thank you very much for participating!	

Appendix 2: OLS Estimates of Three Emprical Models of Spend

Variables	(1) Demographics	(2) + Behaviours	(3) + Attitudes
Age = 30 to 49	11.52	5.739	-1.181
	(9.522)	(9.226)	(10.16)
Age = 50+	31.34***	23.11***	6.236
	(8.898)	(8.700)	(9.835)
Male	-6.451	-1.234	-2.737
	(6.554)	(6.411)	(6.960)
University	-1.908	-6.995	-0.677
	(7.394)	(7.103)	(7.900)
LnHhIncome	9.491**	9.840**	14.05***
	(4.593)	(4.439)	(5.161)
Adults = 2	15.16*	13.71*	10.42
	(7.705)	(7.270)	(8.012)
Adults = 3+	13.78	18.47**	18.03**
	(8.711)	(8.276)	(8.729)
Children	15.02	12.55	10.36
	(9.491)	(9.129)	(9.621)
OutsideDunedin	1.181	0.630	-20.05*
	(10.16)	(9.578)	(11.41)
FreeRange		9.595	3.168
		(6.569)	(7.403)
Organic		18.22***	25.53***
		(6.794)	(7.529)
DrinksEating		-6.909	-16.12**
		(6.619)	(7.487)
LocalOther		9.493	5.669
		(7.141)	(7.736)
Service			11.43
			(8.559)
Quality			7.826
			(7.578)
Fresh			-1.699
			(7.103)
Local			3.701
			(7.685)
Atmosphere			3.973
			(8.010)
Prices			-5.292
			(9.422)
Time			-25.78***
			(8.990)
Weather			-9.794
			(7.302)
Money			-20.17
			(12.42)
Constant	-81.75*	-99.34**	-125.4**
	(44.56)	(43.52)	(49.76)
Interviewer Fixed Effects	no	no	no
P-value for null of Demographic variables jointly zero	0.0000***	0.0001***	0.0018***
P-value for null of Behavioural variables jointly zero		0.0020***	0.0005***
P-value for null of Attitudes variables jointly zero			0.1316
Observations	113	111	96
R-squared	0.332	0.444	0.569
Adjusted R-squared	0.2732	0.369	0.4389

Standard errors appear in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix 3: Average Partial Effects of Two Tobit Models of DiscountChina

Variables	(1) Demographics	(2) + Behaviours
Age = 30 to 49	0.713***	0.588***
	(0.132)	(0.128)
Age = 50+	0.806***	0.672***
	(0.120)	(0.122)
Male	-0.183*	-0.160*
	(0.0936)	(0.0861)
University	0.0306	-0.0239
	(0.0880)	(0.0987)
LnHhIncome	0.0382	0.0667
	(0.0557)	(0.0552)
Adults = 2	-0.417***	-0.426***
	(0.128)	(0.120)
Adults = 3+	-0.0154	0.0288
	(0.0835)	(0.0748)
Children	0.369***	0.341***
	(0.0816)	(0.0964)
OutsideDunedin	-1.113**	-0.773*
	(0.516)	(0.454)
FreeRange		0.0296
		(0.104)
Organic		0.184*
		(0.0974)
DrinksEating		-0.162
		(0.102)
LocalOther		-0.00118
		(0.0928)
P-value for null of Demographic variables jointly zero	0.0000***	0.0000***
P-value for null of Behavioural variables jointly zero		0.0712*
Observations	54	53
Number of censored observations	29	28
Psuedo R-squared	0.5388	0.6125

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Partial effects could not be computed for Attitudes variables

Appendix 4: OLS Estimates of Three Empirical Models of DiscountNZnonlocal

Variables	(1) Demographics	(2) + Behaviours	(3) + Attitudes
Age = 30 to 49	0.0599	0.0530	0.00697
	(0.0653)	(0.0658)	(0.0713)
Age = 50+	0.0704	0.119*	0.0627
	(0.0623)	(0.0676)	(0.0807)
Male	0.0387	0.0373	0.0894
	(0.0474)	(0.0475)	(0.0528)
University	0.0162	0.0510	0.0678
	(0.0503)	(0.0554)	(0.0794)
LnHhIncome	-0.0233	-0.0137	0.0262
	(0.0348)	(0.0368)	(0.0458)
Adults = 2	-0.0742	-0.0642	-0.0795
	(0.0582)	(0.0578)	(0.0650)
Adults = 3+	0.0300	0.0548	0.0472
	(0.0598)	(0.0591)	(0.0630)
Children	0.0482	0.0522	-0.00248
	(0.0764)	(0.0771)	(0.0915)
OutsideDunedin	0.141	0.0588	0.109
	(0.188)	(0.192)	(0.206)
FreeRange		-0.154**	-0.216***
		(0.0578)	(0.0697)
Organic		0.0390	0.0704
		(0.0542)	(0.0633)
DrinksEating		-0.0305	-0.114*
		(0.0515)	(0.0617)
LocalOther		0.0109	-0.0376
		(0.0568)	(0.0681)
Service			0.0667
			(0.0747)
Quality			0.0194
			(0.0737)
Fresh			0.0268
			(0.0637)
Local			0.0691
			(0.0767)
Atmosphere			0.129*
			(0.0728)
Prices			0.0431
			(0.0751)
Time			-0.0930
			(0.0692)
Weather			0.0349
			(0.0579)
Money			0.0449
			(0.0898)
Constant	0.230	0.165	-0.287
	(0.348)	(0.357)	(0.427)
Interviewer Fixed Effects	no	no	no
P-value for null of Demographic variables jointly zero	0.7041	0.4695	0.4156
P-value for null of Behavioural variables jointly zero		0.1314	0.0206
P-value for null of Attitudes variables jointly zero			0.4347
Observations	56	55	53
R-squared	0.121	0.260	0.450
Adjusted R-Squared	-0.051	0.026	0.047

Standard errors appear in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 5: OLS Estimates of Three Empirical Models of LnWTPNZ for Chow Test

Variables	(1) Demographics	(2) + Behaviours	(3) + Attitudes
LnWTPChina	1.047***	0.956***	0.798
	(0.232)	(0.230)	(0.477)
China_Positive	-0.312	-3.365	2.844
	(2.590)	(2.957)	(5.276)
Age = 30 to 49	-0.0135	-0.0137	-0.103
	(0.259)	(0.263)	(0.328)
Age = 50+	-0.461	-0.325	-0.905*
	(0.291)	(0.301)	(0.502)
Male	-0.329	-0.410*	0.0602
	(0.225)	(0.230)	(0.404)
Male * China_Positive	0.545*	0.581*	0.145
	(0.323)	(0.322)	(0.440)
University	-0.598***	-0.928***	-0.895**
	(0.215)	(0.231)	(0.324)
University * China_Positive	0.600*	0.818**	0.481
	(0.315)	(0.392)	(0.620)
LnHhIncome	0.212	-0.111	0.784
	(0.218)	(0.251)	(0.501)
LnHhIncome * China_Positive	-0.233	0.0512	-0.489
	(0.253)	(0.280)	(0.467)
Adults = 2	-0.0952	0.125	-0.696
	(0.265)	(0.293)	(0.573)
Adults = 3+	0.00288	0.0722	0.218
	(0.198)	(0.195)	(0.267)
Adults = 2 * China_Positive	0.589	0.297	0.697
	(0.408)	(0.471)	(0.725)
Children	0.133	0.696**	-0.405
	(0.295)	(0.332)	(0.617)
FreeRange		-0.455	-0.103
		(0.303)	(0.372)
FreeRange * China_Positive		0.382	0.514
		(0.459)	(0.627)
Organic		-0.206	0.429
		(0.293)	(0.520)
Organic * China_Positive		0.457	-0.0950
		(0.402)	(0.681)
DrinksEating		-0.692**	-0.562
		(0.319)	(0.412)
DrinksEating * China_Positive		0.821*	-0.0574
		(0.415)	(0.613)
LocalOther		0.814***	0.463
		(0.234)	(0.331)

Appendix 5 Continued: OLS Estimates of Three Empirical Models of LnWTPNZ for Chow Test

Variables	(1) Demographics	(2) + Behaviours	(3) + Attitudes
LocalOther * China_Positive		-0.732*	-0.542
		(0.367)	(0.509)
Service			0.167
			(0.325)
Quality			-0.295
			(0.296)
Fresh			-0.412
			(0.324)
Fresh * China_Positive			0.0706
			(0.560)
Local			-0.457
			(0.485)
Local * China_Positive			0.760
			(0.686)
Atmosphere			0.113
			(0.395)
Atmosphere * China_Positive			0.321
			(0.505)
Prices			0.911
			(0.772)
Prices * China_Positive			-1.223
			(0.867)
Time			-0.390
			(0.254)
Weather			0.129
			(0.351)
Weather * China_Positive			-0.246
			(0.478)
Money			-0.0661
			(0.378)
Constant	0.242	3.697	-5.192
	(2.265)	(2.724)	(5.308)
P-value for Chow test	0.0479**	0.0601*	0.4785
Observations	55	54	52
R-squared	0.567	0.707	0.855
Adjusted R-squared	0.4150	0.4998	0.5084

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Interactions with China_Positive and Age = 30 to 49, Age = 50+, Adults = 3, Service, Quality, Time and Money deleted due to having fewer than five observations in each category

Appendix 5 Continued: OLS Estimates of Three Empirical Models of LnWTPNZ for Chow Test

Variables	(1) Demographics	(2) + Behaviours	(3) + Attitudes
LocalOther * China_Positive		-0.732*	-0.542
		(0.367)	(0.509)
Service			0.167
			(0.325)
Quality			-0.295
			(0.296)
Fresh			-0.412
			(0.324)
Fresh * China_Positive			0.0706
			(0.560)
Local			-0.457
			(0.485)
Local * China_Positive			0.760
			(0.686)
Atmosphere			0.113
			(0.395)
Atmosphere * China_Positive			0.321
			(0.505)
Prices			0.911
			(0.772)
Prices * China_Positive			-1.223
			(0.867)
Time			-0.390
			(0.254)
Weather			0.129
			(0.351)
Weather * China_Positive			-0.246
			(0.478)
Money			-0.0661
			(0.378)
Constant	0.242	3.697	-5.192
	(2.265)	(2.724)	(5.308)
P-value for Chow test	0.0479**	0.0601*	0.4785
Observations	55	54	52
R-squared	0.567	0.707	0.855
Adjusted R-squared	0.4150	0.4998	0.5084

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

OutsideDunedin and Interactions with China_Positive and Age = 30 to 49, Age = 50+, Adults = 3+, Children, Outside Duedin, Service, Quality, Time and Money deleted due to having fewer than five observations in each category

Appendix 6: OLS Estimates of Three Empirical Models of LnWTPNZ for Chow Test

Variables	(1) Demographics	(2) + Behaviours	(3) + Attitudes
LnWTPUSA	1.152***	1.047***	0.320
	(0.219)	(0.204)	(0.624)
USA_Positive	-0.250	-2.584	-6.537
	(2.545)	(2.586)	(7.018)
Age = 30 to 49	-0.491	-0.575	0.511
	(0.372)	(0.347)	(0.424)
Age = 50 +	-1.189***	-1.215***	-0.0506
	(0.372)	(0.363)	(0.573)
Age = 30 to 49 * USA_Positive	0.494	0.619	-0.523
	(0.507)	(0.475)	(0.684)
Age = 50 + * USA_Positive	1.386***	1.534***	-
	(0.462)	(0.439)	-
Male	-0.302	-0.246	-0.656
	(0.232)	(0.228)	(0.477)
Male * USA_Positive	0.447	0.271	0.601
	(0.340)	(0.337)	(0.461)
University	-0.757***	-1.016***	-1.612**
	(0.215)	(0.218)	(0.622)
University * USA_Positive	0.636**	0.730	1.783
	(0.312)	(0.434)	(1.851)
LnHhIncome	0.348	0.0397	-0.189
	(0.219)	(0.231)	(0.770)
LnHhIncome * USA_Positive	-0.304	-0.0826	0.226
	(0.247)	(0.244)	(0.623)
Adults = 2	-0.0515	0.192	0.395
	(0.263)	(0.265)	(0.835)
Adults = 3 +	-0.000436	0.0943	0.378
	(0.218)	(0.219)	(0.479)
Adults = 2 * USA_Positive	0.214	-0.0421	-0.195
	(0.378)	(0.380)	(0.998)
Children	0.153	0.632**	1.177
	(0.269)	(0.286)	(0.936)
OutsideDunedin	0.119	0.112	-1.409
	(0.642)	(0.645)	(2.265)
FreeRange		-0.298	-0.609
		(0.264)	(0.423)
FreeRange * USA_Positive		0.271	-0.105
		(0.410)	(1.417)
Organic		-0.165	-0.330
		(0.262)	(0.738)
Organic * USA_Positive		0.379	0.844
		(0.354)	(1.242)
DrinksEating		-0.588**	-1.278**
		(0.272)	(0.503)
DrinksEating * USA_Positive		0.850**	1.592
		(0.381)	(1.231)
LocalOther		0.804***	0.840
		(0.209)	(0.503)
LocalOther * USA_Positive		-0.701**	-0.909
		(0.318)	(0.628)

Appendix 6 Continued: OLS Estimates of Three Empirical Models of LnWTPNZ for Chow Test

Variables	(1) Demographics	(2) + Behaviours	(3) + Attitudes
Service			-0.281
			(0.337)
Service * USA_Positive			0.277
			(1.340)
Quality			-1.186*
			(0.600)
Quality * USA_Positive			1.954
			(1.669)
Fresh			-0.708
			(0.569)
Fresh * USA_Positive			0.810
			(1.325)
Local			-1.688*
			(0.829)
Local * USA_Positive			1.725
			(1.022)
Atmosphere			-0.518
			(0.671)
Atmosphere * USA_Positive			0.551
			(0.868)
Prices			-1.118
			(1.112)
Prices * USA_Positive			0.867
			(1.272)
Time			0.0770
			(0.312)
Time * USA_Positive			-1.434
			(1.134)
Weather			-0.202
			(0.351)
Weather * USA_Positive			-0.360
			(0.784)
Money			-0.124
			(0.437)
Constant	-0.617	2.576	7.497
	(2.280)	(2.484)	(8.897)
P-value of Chow test	0.0065***	0.0051***	0.3619
Observations	51	50	48
R-squared	0.682	0.825	0.952
Adjusted R-squared	0.5183	0.6428	0.622

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Interactions between USA_Positive and Adults = 3+, Children, OutsideDunedin and Money deleted due to having fewer than five observations in each category

Appendix 7: OLS Estimates of Three Emprical Models of LnAnnualSpend with Interviewer Fixed Effects and Hour

Variables	(1) Demographics	(2) + Behaviours	(3) + Attitudes
1.interviewer	1.632**	1.276*	1.428**
	(0.705)	(0.706)	(0.669)
2.interviewer	0.331	0.354	0.367
	(0.658)	(0.650)	(0.610)
3.interviewer	0.542	0.546	0.943
	(0.615)	(0.606)	(0.601)
4.interviewer	0.574	0.110	0.287
	(0.672)	(0.687)	(0.633)
5.interviewer	0.749	0.459	0.672
	(0.684)	(0.720)	(0.716)
6.interviewer	0.833	0.659	0.685
	(0.652)	(0.654)	(0.678)
7.interviewer	-0.880	-0.845	-0.575
	(0.838)	(0.832)	(0.760)
Hour	-0.278**	-0.200	-0.302**
	(0.115)	(0.121)	(0.138)
Age = 30 to 49	0.789*	0.749*	0.513
	(0.444)	(0.440)	(0.442)
Age = 50+	1.038**	0.892*	0.00297
	(0.461)	(0.451)	(0.449)
Male	-0.0327	0.0875	0.0837
	(0.332)	(0.334)	(0.323)
University	-0.0622	-0.209	-0.270
	(0.345)	(0.346)	(0.346)
LnHhIncome	0.857***	0.738***	0.960***
	(0.241)	(0.240)	(0.248)
Adults = 2	-0.117	-0.161	-0.310
	(0.379)	(0.368)	(0.363)
Adults = 3+	0.0280	0.118	0.354
	(0.429)	(0.420)	(0.395)
Children	-0.678	-0.438	-0.593
	(0.457)	(0.454)	(0.410)
OutsideDunedin	-1.881***	-1.700***	-1.531***
	(0.565)	(0.556)	(0.550)
FreeRange		0.586	-0.0227
		(0.359)	(0.347)
Organic		0.112	0.289
		(0.341)	(0.335)
DrinksEating		-0.570	-1.249***
		(0.349)	(0.352)

Appendix 7 Continued: OLS Estimates of Three Emprical Models of LnAnnualSpend with Interviewer Fixed Effects and Hour

Variables	(1) Demographics	(2) + Behaviours	(3) + Attitudes
LocalOther		0.378	0.303
		(0.340)	(0.332)
Service			0.148
			(0.375)
Quality			0.376
			(0.380)
Fresh			-0.276
			(0.349)
Local			0.141
			(0.381)
Atmosphere			-0.0774
			(0.383)
Prices			-1.145**
			(0.440)
Time			-0.842*
			(0.482)
Weather			0.0729
			(0.377)
Money			-0.415
			(0.510)
Constant	-1.024	-0.796	-0.836
	(2.420)	(2.419)	(2.414)
Interviewer Fixed Effects			
P-value for null of Demographic variables jointly zero	0.0000***	0.0008***	0.0125**
P-value for null of Behavioural variables jointly zero		0.0908*	0.0038***
P-value for null of Attitudes variables jointly zero			0.0308**
P-value for null of interviewer effects jointly zero	0.0713*	0.1965	0.0887*
Observations	86	86	76
R-squared	0.551	0.603	0.752
Adjusted R-Squared	0.4382	0.4724	0.5862

Standard errors appear in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix 8: OLS Estimates of Three Empirical Models of LnAnnualSpend for Chow Test

Variables	(1) Demographics	(2) + Behaviours	(3) + Attitudes
Online	11.33	13.61*	14.86
	(7.714)	(7.614)	(24.02)
Age = 30 to 49	0.454	0.607	0.210
	(0.459)	(0.421)	(0.457)
Age = 50 +	1.212***	1.033**	0.165
	(0.443)	(0.400)	(0.437)
Age = 50 + * Online	0.173	0.628	0.0362
	(1.048)	(1.151)	(1.415)
Male	-0.195	-0.225	-0.282
	(0.311)	(0.290)	(0.314)
University	0.218	-0.107	0.103
	(0.364)	(0.328)	(0.346)
University * Online	-0.522	0.566	2.544
	(1.322)	(1.229)	(1.637)
LnHhIncome	0.801***	0.699***	0.853***
	(0.229)	(0.208)	(0.234)
LnHhIncome * Online	-1.079	-1.366*	-1.748
	(0.757)	(0.732)	(2.300)
Adults = 2	-0.222	-0.0986	-0.104
	(0.386)	(0.342)	(0.364)
Adults = 3	0.164	0.274	0.493
	(0.412)	(0.371)	(0.390)
Adults = 2 * Online	2.675**	2.400**	3.376
	(1.155)	(1.134)	(3.840)
Children	-0.429	-0.411	-0.659
	(0.449)	(0.408)	(0.436)
OutsideDunedin	-2.206***	-2.102***	-2.125***
	(0.513)	(0.459)	(0.500)
FreeRange		0.735**	0.272
		(0.302)	(0.333)
FreeRange * Online		-0.132	1.299
		(1.471)	(2.440)
Organic		0.0798	0.356
		(0.315)	(0.338)
DrinksEating		-0.523*	-0.890***
		(0.303)	(0.334)
LocalOther		0.270	0.208
		(0.319)	(0.334)
Service			0.453
			(0.387)

Appendix 8 Continued: OLS Estimates of Three Empirical Models of LnAnnualSpend for Chow Test

Variables	(1) Demographics	(2) + Behaviours	(3) + Attitudes
Quality			0.534
			(0.344)
Fresh			0.143
			(0.321)
Local			0.408
			(0.354)
Local * Online			-0.258
			(1.464)
Atmosphere			-0.129
			(0.359)
Prices			-0.663
			(0.407)
Time			-1.412***
			(0.425)
Weather			-0.557*
			(0.322)
Money			-0.265
			(0.542)
Constant	-2.680	-1.891	-2.745
	(2.219)	(2.016)	(2.253)
P-value of Chow Test	0.0944*	0.2093	0.2650
Observations	113	111	96
R-squared	0.437	0.554	0.649
Adjusted R-squared	0.3562	0.4611	0.4944

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Interactions of Online with Age = 18 to 29, Male, Adults = 3, OutsideDunedin, DrinksEating, Quality, Fresh, Atmosphere, Prices, Time, Weather and Money deleted due to having fewer than five respondents in each category. Interactions of Online with Organic and LocalOther persist to be dropped due to collinearity

Appendix 9: 2SLS Estimation of Two Emprical Models of LnAnnualSpend

Variables	(1) + Behaviours	(2) + Attitudes
Age = 30 to 49	1.069	0.811*
	(0.653)	(0.474)
Age = 50+	1.103*	0.405
	(0.631)	(0.496)
Male	0.176	0.324
	(0.492)	(0.343)
University	-0.0350	-0.132
	(0.416)	(0.327)
LnHhIncome	0.584*	0.747***
	(0.316)	(0.284)
Adults = 2	-0.141	-0.0973
	(0.390)	(0.348)
Adults = 3+	0.352	0.634*
	(0.415)	(0.350)
Children	-0.275	-0.615
	(0.486)	(0.388)
OutsideDunedin	-1.683**	-1.411***
	(0.658)	(0.531)
FreeRange	0.901	0.581
	(1.194)	(0.966)
Organic	-0.262	0.0514
	(1.089)	(0.649)
DrinksEating	-1.905	-1.963**
	(1.496)	(0.998)
LocalOther	0.277	0.316
	(0.606)	(0.630)
Service		0.237
		(0.355)
Quality		0.637*
		(0.358)
Fresh		-0.283
		(0.328)
Local		0.519
		(0.361)
Atmosphere		0.220
		(0.413)
Prices		-0.669*
		(0.393)
Time		-1.391***
		(0.474)
Weather		0.0129
		(0.313)
Money		-0.315
		(0.596)
Constant	-0.444	-1.730
	(2.882)	(2.542)
Interviewer Fixed Effects	no	no
P-value for null of Demographic variables jointly zero	0.0006***	0.0064***
P-value for null of Behavioural variables jointly zero	0.0256**	0.0045***
P-value for null of Attitudes variables jointly zero		0.0030***
Observations	85	75
R-squared	0.443	0.631

Standard errors appear in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix 10: Linear Regression of WTPNZ with Endogenous Binary Treatment Effect (WTPChina > 0)

Variables	WTPNZ	Treatment (WTPChina > 0)
WTPChina	1.269***	
	(0.359)	
Age = 30 to 49	-2.337	-2.543***
	(2.485)	(0.767)
Age = 50+	-4.881*	-3.239***
	(2.593)	(0.953)
LnHhIncome	0.851	-0.880**
	(1.054)	(0.449)
Children	0.323	-1.807
	(2.414)	(1.165)
University	-2.776*	0.132
	(1.575)	(0.606)
Adults = 2	0.439	2.865***
	(1.983)	(0.969)
Adults = 3+	-2.194	0.611
	(1.926)	(0.913)
OutsideDunedin	1.916	16.89
	(3.381)	(0)
DrinksEating	-0.928	0.913
	(1.591)	(0.669)
WTPChina > 0	-8.881***	
	(3.028)	
Constant	3.987	9.601**
	(10.85)	(4.507)
Observations	57	57

Standard errors appear in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Wald test of independent equations returns a p-value of 0.5606, i.e. we cannot reject the null hypothesis of no correlation between the treatment errors and the outcome errors

This model only can only be estimated with a smaller set of variables than we would like to include such as the ones reported.