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Effect of online shopping on consumers' shopping travel and goods' last-mile travel: A case study in Christchurch

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Abstract

The unprecedented growth of online shopping in recent years has the potential to change the shopping-related travel of people and the pattern of goods movement in urban areas. As online shopping provides consumers with the opportunity to buy things without having to travel to the physical shops, it might reduce consumers' in-store shopping trips. However, consumers might visit the shops to check and/or inspect products before buying them online. Also, a huge number of parcels containing items sold online must be transported to end-consumers' doorsteps, using light freight vehicles, and a clear understanding of the travel implications of online shopping is essential to help estimate the demand for shopping travel and goods' transport. The previous empirical studies have reported mixed observations as to the effect on in-store shopping travel of online shopping. Moreover, the previous studies did not consider consumer attitudes towards missing 'attended' deliveries (i.e. deliveries that require signature on receipt) and alternate modes of unattended delivery (e.g. collection and delivery points), which appear to affect both consumers' in-store shopping travel and goods' last-mile travel. This study is aimed at investigating the effect of the above factors, in addition to various socio-demographic, travel and shopping-related factors, on in-store shopping travel and goods' last-mile travel. Data from 355 consumers residing in Christchurch were obtained through an online survey. The analysis has been carried out, using non-parametric tests and ordinal logistic (OL) regression. Consumers' travel for in-store shopping or collecting items from collection and delivery points (CDPs) were not found to be significantly correlated with their online shopping frequency. However, the delivery service provider's transport was found to be increasing with an increase in online shopping. These insights on the interaction of online shopping and transport are expected to be helpful to transport planners in forecasting the demand for personal and goods transport.

1 Introduction

With the advancements in Information and Communication Technology (ICT), consumers' accessibility to internet-based applications, such as telecommuting, e-commerce, e-education and information searching, have greatly improved. For instance, the internet has penetrated 51% of the world population (International Telecommunication Union, 2018). This is apparently due to ICT allowing consumers to participate in various activities without travelling.

Online shopping has grown rapidly, in terms of the number of online shoppers and online retail sales worldwide. For example, the global 'online retail sales', as a proportion of total retail spending, has been increasing and is estimated to surpass 16% by 2021, compared to 7.4% in 2016 (eMarketer, 2017). Online shopping overcomes spatial and temporal constraints, by allowing consumers to purchase goods and services at any time, without having to travel to physical shops (Mokhtarian, 1990), and thus it can potentially reduce the demand for shopping travel. However, consumers might visit the physical shops to check and/or compare the products before buying, or to pick the products up after buying them online, hence undermining the potential reduction in shopping trips saved by shopping online (Mokhtarian, 2009). In addition to this, online shopping generates freight vehicle trips, as the items sold online are often required to be delivered to the consumers' doorsteps (Visser and Nemoto, 2003). For instance, in December 2017, NZ Post delivered 38.9 million parcels (up by 9% from 2016) across the country (New Zealand Post, 2017). Therefore, online shopping is likely to have implications for both shopping travel and goods' last mile transport, which constitute a substantial portion of total urban travel. For example, in New Zealand, shopping trips constituted 22% of all the trips undertaken by households, and 61% of those trips were done by car (O'Fallon and Sullivan, 2009).

It should also be noted that the per capita vehicle ownership in New Zealand is very high (about 0.77) (Ministry of Transport, 2016), and so is the reliance on car for travel (Kedia et al., 2017). For instance, in 2010, trips by car (as a driver or passenger) accounted for 64% of all the trips made and 78% of the total distance travelled in New Zealand (Milne et al., 2011). It is a major cause of rapidly growing traffic congestion and transport emissions. Therefore, an assessment of the impacts of growing online shopping on the travel pattern of people, as well as on goods' movement, is essential to help forecast passenger and freight travel demand, and to help frame appropriate transport policies. For example, it will help revisiting kerbside parking and land-use regulations to accommodate the increasing demand for commercial road-side parking required for the delivery of parcels in residential areas (Escand et al., 2018).

Several studies (e.g. Farag et al., 2006; Ferrell, 2004; Lenz, 2003; Sim and Koi, 2002; Xi et al., 2018; Zhang et al., 2007; Zhou and Wang, 2014) have explored the interaction between online shopping and consumer shopping travel. However, the nature of the nett effect on travel due to online shopping is not clear, and a wide variety of observations have been reported. For example, Shi et al. (2019) found that online shopping reduced shopping travel, while Lee et al. (2017) and Rotem-Mindali (2010) observed an increase in shopping travel. The differences reported in previous studies regarding the interaction between traditional in-store shopping and online shopping can be attributed to several reasons, such as differences in the geographical and cultural contexts and differences in sample size and composition.

It is important to also note that a large proportion of last-mile deliveries fail during the first attempt, due to recipients not being available when a delivery is attempted, and thus one or more re-delivery attempts are required to deliver the items successfully (Kedia et al., 2019). This increases the service providers' delivery cost and vehicle-kilometres (Kiousis et al., 2019), and may lead to an unsustainable last-mile delivery system (Nathanail et al., 2018). Collection and Delivery Points (CDPs) at third-party locations, such as local businesses, have been popular in European countries as an efficient method for reducing the costs and transport emissions for each parcel

delivered (Morganti et al., 2014). However, they have only recently (i.e. 2016) been introduced in New Zealand. Therefore, understanding the effect of consumer attitudes towards missing attended deliveries and using CDPs to receive their parcels, on their online shopping frequency, is needed to estimate the likely impacts on consumer shopping travel and delivery vehicles movement.

The previous empirical studies examined the effect of online shopping only on the travel required to do in-store shopping, but not the effects on travel required to collect parcels from pick-up locations (e.g. CDPs) and delivery-vehicles' transport. This study considered consumer attitudes towards missing attended deliveries and perceptions of using CDPs, as explanatory variables for modelling consumers' online shopping frequency. This will help identify the characteristics of online shoppers, with respect to missing attended deliveries and attitude to collecting parcels from CDPs, so the likely effect on travel by consumers collecting parcels from CDPs and delivery vehicle travel can be estimated. Also, previous studies adopted a variety of statistical methods, such as descriptive statistics (e.g. chi-square tests), logistic regression, linear regression, and structural equation modelling (SEM). This study adopted descriptive statistics and logistic regression, but differs from the others, as it examines the effects on in-store shopping travel, on travel to collect parcels from CDPs, and delivery-vehicle travel. To the best of the authors' knowledge, it is the first study done in New Zealand that explores whether online shopping reduces the demand for both shopping travel and delivery-vehicle travel.

The remainder of this paper is organised as follows. Section 2 describes the previous empirical studies aimed at understanding the interplay between online shopping and in-store shopping travel. The design and administration of the survey are discussed in Section 3. The determinants of online shopping are identified, using non-parametric tests and the ordinal logistic (OL) regression in Section 4. Section 5 contains the conclusions arising from the study.

2 Empirical Studies – Review

Though the general belief is that online shopping leads to *substitution* of shopping travel, it may also result in other types of interactions, such as *complementarity*, *modification*, and *neutrality*. Salomon (1986) and Mokhtarian (1990), defined these interaction types as follows. *Substitution* occurs when a location-based activity is substituted by an ICT-based counterpart, thus eliminating one's need to travel. *Complementarity* (enhancement) refers to the generation of travel when ICT leads one to conduct new location-based activities, which would not have occurred otherwise. *Neutrality* (or a neutral effect) happens when ICT does not affect other travel-based activities. For example, not all the alternatives to ICT-based activities are travel-based (e.g. not every distance-learning student would otherwise be enrolled at a conventional university campus). *Modification* refers to the change in travel parameters such as trip timing, mode, and route, due to the ICT use.

A substitution effect has been reported in several studies. One of the very few panel studies (Lenz, 2003), assessed the potential traffic substitution due to online shopping in the Stuttgart region, using a descriptive statistics approach. Respondents were classified based on socio-demographic characteristics and affinity towards e-commerce. A reduction of less than 10% of the total personal shopping travel was reported to have occurred. Ferrell (2005) found home teleshopping to have substitutional effects on out-of-home shopping travel. The

activity-based approach considered work, maintenance, discretionary, shopping, and travel activities as variables in SEM. Online shoppers were found to have made fewer shopping trips and travel shorter distances for shopping purposes (i.e. modification).

Unlike other studies, where the effect of online shopping for only one product was considered, Weltevreden (2007) examined the impact of buying a variety of products online, on in-store shopping at city centres in the Netherlands, using a descriptive analysis approach. About 22% of online shoppers revealed that online shopping caused them to make fewer trips to the city centre, thereby indicating a substitutional effect. Many online searchers (30%) and online shoppers (48%) indicated that they spend less time shopping in a city centre, perhaps because they had already gathered information at home (i.e. modification). One of the few studies done in developing countries, Irawan and Wirza (2015), applied the SEM technique to the data obtained from online shoppers in Indonesia, and found online shopping to have substituted in-store shopping trips. Similarly, another recent study in the context of developing countries where online shopping is growing rapidly, Shi et al. (2019), investigated whether e-shopping for four types of goods (i.e. clothes and shoes, electronics, food and drink, and cosmetics) replaces shopping trips in Chengdu, China, using regression models. Socio-demographics, internet experience, car ownership, and location factors were found to be influencing the in-store and online shopping frequencies. Online shopping had a substitutional effect on the frequency of shopping trips.

The studies supported the notion of substitutional effects of online shopping on in-store shopping travel. In contrast to this, there are studies that found online shopping to have a complementary effect on traditional in-store shopping. For instance, a study by Casas et al. (2001) compared the travel behaviour of online shoppers (those who purchased a product or searched product information online) and non–online shoppers, using a descriptive analysis of the data obtained from the Household Travel Survey conducted in Sacramento, USA. Online shoppers were found to have made insignificantly more trips in general, as well as more shopping trips than non-online shoppers, probably because of their active lifestyle. Ferrell (2004), using a linear regression approach, estimated the complementary effect of teleshopping on traditional out-of-home shopping trips, person miles travelled for shopping, and shopping-trip chaining. Households doing teleshopping were found to have engaged in more shopping trips and to chain more of their shopping trips.

Farag et al. (2005) investigated the interplay between consumers' online shopping pattern (i.e. frequency of online searching and online shopping) and non-daily shopping trips, after controlling for socio-demographic, land use, behavioural, and attitudinal characteristics of consumers in the Netherlands. Path Analysis was used to model the direct and indirect effects. Complementarity between online shopping and in-store shopping appeared to be more likely than substitution. Online searching was reported to be positively correlated with non-daily shopping trips. Using the data from the previous study, Farag et al. (2007) applied SEM with latent variables to identify the relationship between online shopping (i.e. searching and buying) and in-store shopping. As with their previous observations, the results of this study also indicated a complementary effect on trips.

Applying an ordered logit model, Rotem-Mindali (2010) investigated the shopping mode choice behaviour of consumers having different levels of affinity to ICT, for

buying electrical products, in the Tel Aviv metropolitan area. Online shopping was found to be serving as a complementary option to traditional shopping. Cao et al. (2011), applying the SEM technique on the data obtained from consumers in the Minneapolis / St. Paul metropolitan area, found online searching frequency to increase both online shopping and in-store shopping. However, online shopping was also found to have positive correlation with in-store shopping, which may be attributed to consumers checking the goods in-store and then purchasing them online, due for example to an item being available at a cheaper price online. Online searching increased the in-store shopping frequency more than the increase in the in-store shopping frequency caused by online shopping.

A similar approach (i.e. using the SEM method) by Zhou and Wang (2014) resulted in a complementary relation between online shopping and personal shopping trips. This study used the data from the first ever National Household Travel Survey in the USA that included detailed information on consumers' ICT usage and online shopping. Exogenous variables included individual, household, regional, internet usage, and travel characteristics. The 'propensity to purchase online' was derived from web use and online purchase frequency, and the 'propensity for shopping trips' was derived from the total number of trips and shopping trips. Both the variables were used as the latent endogenous variables. The 'propensity to purchase online' was found to be positively correlated with the 'propensity for shopping in-store'.

Ding and Lu (2015) applied the SEM technique to the data for Chinese consumers in Beijing. Endogenous variables were categorized into three groups: online shopping behaviour, in-store shopping behaviour and other activity travel (e.g. leisure activity frequency). Exogenous variables included socio-demographic characteristics and shopping accessibility (i.e. shopping opportunities within 500m radius of home). Online shopping frequency was found to have a positive correlation with the frequency of in-store shopping and frequency of online searching. Online shoppers (who buy online at least once a week) were found to be likely to make fewer leisure trips (i.e. modification). Zhen et al. (2016) applied a joint ordered probit model to the data for online shoppers in Nanjing, China, and concluded that online shopping increased the in-store purchasing for all four types of products considered (i.e. clothing, books, daily goods, and electronics), even after controlling for shopping attitudes and demographics. The magnitude of the complementarity effect differed by product type, with less frequently purchased products showing a larger effect. Lee et al. (2017) studied the effect of personal characteristics, attitudes, perceptions, type of shopping settings (i.e. retail profile and consumer accessibility to shops), and the built environment on frequencies of shopping online in Davis, USA. Copula-based ordered response models suggested that online shopping had a complementary relationship with in-store shopping frequency, after controlling for demographic variables and attitudes.

There have been a few studies where no significant effect of online shopping on shopping travel was found (i.e. a neutral effect on travel). For example, Sim and Koi (2002) used factor analysis and descriptive statistics methods for data obtained from Singaporean online shoppers, and based on their demographic characteristics and attitudes toward internet use and online shopping, found online shopping not to have a significant impact on traditional shopping patterns, primarily due to Singaporeans' preference for in-store shopping. Hiselius et al. (2012) also adopted a descriptive analysis approach and utilised the web-survey data obtained from online shoppers in Sweden for analysing the changes in consumers' travel pattern. Respondents were

categorised as regular online shoppers (i.e. shop online at least once per week) and non-regular online shoppers (i.e. shop online less than once a week or never shop online). No significant difference was found in total trips and individual trip lengths, except for mode choice, thereby supporting the concept of neutrality. Calderwood and Freathy (2014) examined the effect of online shopping upon the number of their shopping trips, using the Scottish isles as a case study. Factors, such as drive-time to the shopping center in the main town, the availability of broadband internet connection, and the number of retail shops available on each island, were considered in the cluster analysis. Though there was some evidence that internet adoption reconfigured travel patterns, the overall impact upon mobility was found to be modest. Although the findings noted both substitution and generation effects, online shopping appeared to have a neutral outcome for the majority of island residents. Another study by Hiselius et al. (2015) investigated the in-store shopping travel behaviour of frequent, regular, and infrequent online shoppers in Sweden. In addition to the frequency of shopping trips, distance travelled and mode used for shopping trips were also considered as explanatory variables. The results indicated that frequent online shoppers make as many trips to physical stores as infrequent online shoppers, but by more sustainable modes of transport (e.g. walking and cycling), and frequent online shoppers travel shorter distances in cars for shopping trips than infrequent online shoppers. Thus, online shopping was found to have both a neutral effect (on frequency of trips) and a substitutional effect (on distance travelled) for in-store shopping travel. Similarly, a recent study of Chinese online shoppers, Xi et al. (2018), adopted the SEM technique and found online shopping to have a neutral effect on consumers' in-store shopping travel.

Modification effects have been observed in combination with other types of interaction effects in several studies. For instance, online searching was found to have decreased the shopping duration, which may be due to the information gathered by consumers prior to visiting the stores (Farag et al., 2006). Similarly, modification in shopping time and shopping distance by female households was found to have taken place as a result of online shopping in Ferrell (2005). Online shoppers were observed to have a shorter shopping duration in Farag et al. (2007) and Weltevreden (2007), and shorter distances travelled by car for shopping trips (Hiselius et al., 2015).

The variations in the results of the above studies can to a large extent be attributed to differences in the formulation of dependent and independent variables, geographical context, statistical methods used, sample size and composition, type of commodity, and the definition of online shoppers (Suel and Polak, 2018). It must be noted that to the best of authors' knowledge, the previous studies did not consider the consumer attitudes towards missing attended deliveries and alternate modes of unattended deliveries into account while examining the travel implications of online shopping.

3 Survey Design and Implementation

An online survey was administered in May – June 2018 to panel members of a market research firm, using the *Qualtrics* software package. To be eligible to participate in the survey, respondents had to be at least 18 years old, residing in Christchurch and must have bought online in 12 months prior to completing the survey. The questionnaire comprised questions about socio-demographic characteristics, in-store and online shopping characteristics, travel characteristics,

and attitude towards missing attended deliveries (i.e. deliveries requiring signature on receipt) and alternate modes of unattended delivery (i.e. collection and delivery points). All the online shopping related questions were to be answered regarding products that cannot be delivered via the internet (i.e. travel tickets and hotel bookings were excluded). The flow of questions was programmed such that only relevant questions appeared to each respondent based on their initial responses, to achieve a balance between the information being sought and the burden on respondents (Kusumastuti et al., 2011). A total of 418 responses were obtained from the panel members, but only 305 of them were used for the analysis, as 113 were not fully completed. In addition to the online survey, another online survey, comprising the same sets of questions, was simultaneously conducted among the acquaintances of the authors. Around 100 responses were obtained, out of which only 50 were complete and able to be used for the analysis. Therefore, the dataset used in the analysis comprised 355 complete responses obtained from the two different sources.

The variables considered in the study are described below. The variable levels were decided based on Census information (wherever applicable). However, some levels of several variables were later amalgamated due to their 'expected count' value being less than five, which is a necessary condition for the results of the descriptive tests to be robust.

Socio-demographic characteristics included individual-specific information (e.g. gender, age, educational qualification, employment status) and household-specific information (e.g. type of a dwelling unit, household composition, household size, number of workers in household, number of children below 18 years and below 13 years of ages in household). Table 1 compares the sample and census proportions and shows that the sample represents the population reasonably well.

Table 1 Sample characteristics

Factors	Categories	Sample values (%)	Census 2013 (%)
Gender	Male	50.7	49.1
	Female	49.3	50.9
Age (years)	18 – 29	23.4	19.4*
	30 – 39	20.9	16.9
	40 – 49	14.6	18.9
	50 – 59	14.6	17.8
	60 or more	26.5	27.1

Note: *20 – 29 years

Shopping-related information covered aspects of both online shopping and in-store shopping. Online shopping variables included respondent's internet usage (during the past 7 days) regardless of the purpose of use, experience with online shopping (i.e. time since the first online shopping); frequency of online shopping (during the past 12 months); and frequency of searching about products and/or shops online before buying them from physical shops. In-store shopping related information included the frequency of shopping at physical shops; the frequency of examining products and/or checking the price of products in physical shops before buying them online; and the frequency of visiting businesses selling items of frequent use (e.g. supermarkets, petrol stations, dairies, pharmacies and post shops). Travel characteristics covered information, such as individuals' most commonly used travel mode for each of work and shopping trips, and the numbers of cars and cycles available for use in the household.

Consumer attitudes towards missing attended deliveries and perceptions of using CDPs were recorded in terms of responses to qualitative statements, on a five-point Likert scale (i.e. -2 for 'strongly disagree' to 2 for 'strongly agree'). It should be noted that each of the variables in this study were captured on a categorical scale, with some of them (e.g. gender) considered as nominal, and others (e.g. age, attitudinal variables) being considered as ordinal. The attitudinal variables are listed in Table 2.

Table 2 Attitudinal variables

Attitude toward missing attended deliveries and alternate modes of unattended delivery
Missing an attended delivery is an issue for me
Parcels being left unattended in the house compound is undesirable for me
Operating hours of post shops and pharmacies are not sufficient enough to facilitate collection of parcels
I am concerned that getting a parcel redelivered, adds to vehicular traffic and air pollution
I do not mind getting my parcels delivered to a CDP, and collecting them later at a time convenient to me
I would be willing to combine my travel to CDPs with my daily work/education related travel
I would not mind going walking/biking to collect my parcels from a nearby CDP

4 Determinants of Online Shopping

Factors that govern consumers' online shopping frequency were determined, using non-parametric tests and OL regression, as discussed in the following sections.

4.1 Descriptive tests

Consumers were categorized based on their online shopping frequency during the 12-months period prior to the survey, as shown in Table 3. It should be noted that since the response (or dependent) variable and several explanatory variables were ordinal in nature and not normally distributed, parametric tests such as the independent samples t-test and chi-square test for association, which require the data to be normally distributed, could not be used (Scott and Mazhindu, 2005). Thus, non-parametric tests, such as the Jonckheere-Terpstra (JT) test and Kruskal-Wallis H (KWH) test, which do not require the data to be normally distributed, were conducted to determine the correlation between consumers' online shopping frequency and the various characteristics described above. Of the 34 factors considered initially, only ten turned out to be statistically significantly correlated (at the 90% confidence level) with online shopping frequency, and hence the results of only those ten factors are described below, with the detailed results being shown in Appendix 1.

Table 3 Categorisation of consumers

Type of consumers	Definition
Very frequent online shoppers (VFOS)	Those who bought online about once or more per month
Frequent online shoppers (FOS)	Those who bought online about once per three months
Infrequent online shoppers (IFOS)	Those who bought online about once per six months or longer

The JT test is a rank-based non-parametric test that can be used to determine if there is a statistically significant monotonic trend between an ordinal explanatory variable and an ordinal or continuous response variable. The JT test is similar to the KWH test, which is also a rank-based non-parametric test and can be used to assess differences between the response variable scores of two or more levels of an

explanatory variable. However, the JT test accounts for the 'ordinal' nature of the explanatory variable, unlike the KWH test, which considers the explanatory variable to be 'nominal' in nature (Laerd Statistics, 2017).

If the distribution of the response variable for each level of an explanatory variable have the 'same' shape, one can interpret the JT test as a test of 'trend in medians', and the KWH test as a test of 'differences in medians'. However, if the distribution of the response variable for each level of an explanatory variable have a 'similar' shape (for JT test) and a 'different' shape (for KWH test), one can interpret the JT test as a test of 'trend in effects', and the KWH test as a test of 'differences in distributions' (i.e. differences in mean ranks) respectively. In this study, distributions of the response variable for the levels of the explanatory variables were not the 'same', and thus the JT test was considered as a test of 'trend in effects' rather than 'trend in medians', and the KWH test was considered as a test of 'differences in distributions' (i.e. mean ranks). However, the median values (of the response variable) for the ordered levels of each of the explanatory variables are also reported, and the median values should be interpreted cautiously.

The JT test indicated that there was a statistically significant decreasing monotonic trend (i.e. negative Z-value) in 'frequency of online shopping' for increasing levels of age, and an increasing monotonic trend (i.e. positive Z-value) for increasing levels of several variables, namely, number of workers in household, number of children below 18 years of age in household, number of children below 13 years of age in household, internet usage during the past 7 days, time since first online shopping, number of cycles in household, and frequency of missing deliveries.

The KWH test indicated that there were statistically significant differences in the 'frequency of online shopping' (i.e. different mean ranks) for levels of the explanatory variables, namely, household composition and employment status.

4.2 Logistic regression analysis

Since the descriptive statistics does not allow for the effects of multiple variables, the effect of each of the explanatory variables on the response variable cannot be determined. Therefore, an OL regression analysis was carried out to determine the association between consumers' frequency of online shopping and in-store shopping related travel, while controlling for the effects of consumers' socio-demographic, shopping, and travel characteristics, and for their attitude towards missing attended deliveries and perceptions of using CDPs. The frequency of online shopping during the 12-months period prior to the survey was considered as the dependent (or response) variable, and consumers were categorized as VFOS, FOS and IFOS, as shown in Table 3. All the remaining variables were treated as predictor (or explanatory) variables.

Moreover, 34 explanatory variables were initially considered to estimate the model, using the OL regression approach in the Statistical Package for Social Sciences (SPSS). Of the 34 variables, only nine turned out to be statistically significant in explaining the variance in consumers' online shopping frequency, at the end of four iterations of the model estimation, with variables that did not turn out to be statistically significant (at 90% confidence level) being eliminated from the model in the next iteration. The results of the OL regression analysis are given in Appendix 2 and are discussed below.

The VFOS level of the response variable was treated as the reference level. The intercept only model (i.e. with no variables included) was outperformed by the final model (i.e. with variables included), as the likelihood ratio chi-square test, which tests whether at least one of the coefficients is not equal to zero, was found to be statistically significant (chi-square = 78.700, $p < 0.001$, and degrees of freedom = 32). Furthermore, both the Pearson and Deviance chi-square goodness-of-fit measures (p-value of 0.215 and 0.382 respectively) show that the model is an adequate fit. The McFadden Pseudo R^2 value of 0.103 indicates a moderately good fit, as the Pseudo R^2 values are usually considerably lower than the R^2 value of the ordinary least square (OLS) regression (Kusumastuti and Nicholson, 2017). A value between 0.2 and 0.4 denotes an excellent fit for the model, and is approximately equivalent to an OLS R^2 value between 0.5 and 0.8 (Domencich and McFadden, 1975).

OL regression estimates only one model (except for different intercept values) for all the choice alternatives (or levels). The logit estimates (i.e. log-odds) are coefficients of the explanatory variables included in the model and are relative to the reference level within each of the explanatory variables. For example, the log-odds of scoring higher on the response variable (i.e. shopping online more frequently) is 1.0 units higher for consumers aged 18-29 years than those aged 60 years or more, when all the other predictor variables in the model are held constant. In other words, younger consumers are more likely than older ones to buy online ‘very frequently’.

The standard error values of the estimates indicate the average distance of the observed values from the regression line, and thus show the precision of the model on average, using the units of the response variable. Smaller values are better because it indicates that the observations are closer to the fitted relationship.

The odds-ratio is the exponentiation of the logit estimate. It indicates the odds of a level of an explanatory variable (relative to the reference level of the variable) being in a higher level of the response variable than levels lower than that. For example, for respondents aged 18-29 years, the odds-ratio of 2.72 (Appendix 2) indicates that they are 2.72 times more likely to be in the higher level (e.g. VFOS) of the response variable (i.e. frequency of online shopping) than respondents aged 60 years or more.

In line with the results of the JT test and with previous studies (e.g. Clemes et al., 2014; Corpuz and Peachman, 2003), age turned out to be significantly correlated with the frequency of online shopping, with younger consumers found to be more likely to buy online ‘very frequently’. This could be due to young people being more technology-oriented and time-poor to shop in-store.

As observed in the results of the KWH test and in previous studies (e.g. Dahiya, 2012), household composition was found to be significantly correlated with the frequency of online shopping, with people living alone and in households composed of flat-mates only (i.e. not a family home) being less likely to buy online ‘very frequently’ than respondents living in households with other types of compositions.

Household size turned out to be significantly correlated with the frequency of online shopping, which is inconsistent with the result of the JT test. Note that more weight should be placed on the results of OL regression if the results of the descriptive tests are inconsistent with the results of OL regression. Consumers living alone were found to have a greater likelihood of buying online ‘very frequently’. However, this is inconsistent with the above correlation between household composition and

frequency of online shopping, where consumers living alone were found to have a low likelihood of buying online ‘very frequently’. It must be noted that three out of four coefficients for household size did not turn out to be statistically significant, while three of the four coefficients for household composition turned out to be statistically significant, implying a stronger correlation of the latter with the frequency of online shopping.

Consumers’ online shopping experience was found to be positively correlated with the frequency of online shopping, with consumers who began online shopping more than six years ago having a greater likelihood of shopping online ‘very frequently’ than consumers with less experience of online shopping. This is in accordance with the results of the JT test, and also with the observation made by Brown et al. (2003) that previous successful purchases of products via the internet have a direct effect on individuals’ future online purchase intentions. This is possibly due to their familiarity with online shopping platforms and high amount of satisfaction they have achieved by shopping online. On the other hand, consumers who bought online for the first time less than three years ago were found to be least likely to buy online ‘very frequently’. This is possibly due to such consumers’ limited confidence in online shopping.

In contrast to the results of the JT test, the number of cars available in household turned out to be significantly correlated with the frequency of online shopping. Specifically, consumers having no car or three or more cars in their household were more likely to buy online ‘very frequently’ than consumers having one or two cars. This could be due to difficulty in reaching shopping destinations if no car is available because having a car, gives consumers the flexibility to reach shopping destinations conveniently (Ding and Lu, 2015), and perhaps because consumers having three or more cars have a very high disposable income, which enables them to shop more overall, regardless of the mode of shopping.

As observed in the results of the JT test, consumers’ frequency of missing attended deliveries was found to be statistically correlated with their frequency of online shopping. Consumers who missed attended deliveries ‘most of the time’ or ‘always’ were found to have a greater likelihood of shopping online ‘very frequently’ than the other consumers. The cause and effect in this correlation is likely to be the frequency of online shopping, and the frequency of missing attended deliveries, respectively. This can be attributed to consumers with a greater likelihood of buying online ‘very frequently’ being young working adults or students, who are perhaps too time-poor to shop in-store and often unable to receive deliveries due to competing commitments.

Contrary to the results of the JT test, consumers who do not find it undesirable to have a parcel being left unattended in the house compound, were found to be more likely to shop online ‘very frequently’ than those who find it undesirable. This shows that consumers with a greater likelihood of buying online ‘very frequently’ might be buying mainly less expensive items online that they do not need to worry about, or perhaps they have a space in their house compound where parcels can be left unattended without the security of parcels being compromised.

Consumers who agreed with operating hours of post shops and pharmacies not being enough to facilitate collection of parcels, were found to be significantly more likely to shop online ‘very frequently’ than those who disagreed with it. This could be attributed to VFOSs having a high frequency of missing attended deliveries due to not being available to receive their parcels, and consequently having to collect

parcels from the conventional CDPs (i.e. post shops and pharmacies) that operate mainly during 8 am to 5 pm, which perhaps coincides with consumers' working/office hours or with their educational commitments at a school/college. This correlation is inconsistent with the results of the JT test.

Unlike the results of the JT test, consumers who did not agree that getting a parcel redelivered adds to vehicular traffic and air pollution, were found to have a significantly greater likelihood of buying online 'very frequently'. This shows that VFOSs are perhaps more likely to get the failed parcels redelivered, because of their high frequency of missing attended deliveries, and insufficient operating hours of the existing CDPs (i.e. post shops and pharmacies) that makes self-collection of parcels difficult.

From the above discussion, it can be observed that VFOSs often miss attended deliveries and are more inclined towards getting the failed parcels redelivered, because they find it difficult to use CDPs to collect their items bought online, due to the short operating hours of the traditional CDPs (i.e. post shops and pharmacies). This causes the courier service providers to make re-delivery attempts until the parcel is successfully delivered, thereby increasing the travel for each parcel delivered. Hence, the delivery-vehicle transport might be more than required for deliveries done in association with CDPs where consumers collect their parcels.

Consumers' willingness to use CDPs for collecting parcels was not found to be significantly correlated with their online shopping frequency. Moreover, despite another study (Kedia et al., 2019) concluding that CDPs, if located densely around consumer locations, can facilitate consumers collecting their parcels from CDPs on foot or cycle, consumers' willingness to collect parcels on foot or cycle from a nearby CDP, did not turn out to be statistically correlated with the frequency of online shopping. Also, there was no correlation found to exist between consumers' in-store shopping and online shopping frequency, implying a neutral effect of online shopping on consumers' in-store shopping travel.

Therefore, out of the three possible components of shopping-related travel that online shopping was anticipated to affect, two components (i.e. consumers' in-store shopping travel and travel to collect parcels from CDPs) were not found to have been affected significantly as a result of increasing online shopping. However, the effect of online shopping on delivery-vehicles' transport was found to be an overall nett increment in travel.

5 Conclusion

Increasing online shopping worldwide has been changing the way people participate in shopping activities, and in turn has been modifying the demand for personal and goods transport. Thus, the knowledge of the nett effect on both personal and goods transport is necessary to be incorporated in the travel demand estimation processes that are undertaken to predict the requirements for both the consumers' and goods' transport in the future. An ordinal logistic regression approach, supported by the non-parametric JT and KWH tests, was adopted to identify the effects of increasing online shopping on consumer shopping travel and goods' last-mile travel, using Christchurch as a case study. As the descriptive tests do not take into consideration the effect of multiple variables on the response variable at a time, the results of the non-parametric tests are less reliable than the results of the ordinal logistic

regression analysis, which account for the effects of multiple variables. Though there was found to be no significant effect on consumers' in-store shopping travel and travel to collect parcels from CDPs, delivery-vehicles' transport for each parcel sold/bought online is expected to increase with an increase in online shopping. The relationship between the frequency of online shopping with the various explanatory variables (i.e. consumer characteristics), derived in the study, are expected to help online businesses and physical shops understand consumer behaviour and to frame appropriate business strategies. Also, transport planners are expected to benefit from the knowledge created in this study, in terms of understanding the travel behaviour of existing and likely future online shoppers and is a useful step towards forecasting the demand for consumer shopping travel and goods' last-mile travel.

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Appendix – 1: Results of the non-parametric tests

Factors	Number of responses	Statistical test	Mean ranks	Median DV score	Test statistic (df)	Z-value	P-value
Age (years)							
18-29	83	JT Test	--	2.0	21,921.50	-2.87	**0.004**
30-39	74		--	2.0			
40-49	52		--	3.0			
50-59	52		--	2.0			
60 or more	94		--	2.0			
Employment Status							
Student (full or part time)	36	KWH Test	153.83	2.0	10.23 (3)	--	**0.017**
Employed part time	50		185.50	2.0			
Employed full time	131		196.36	2.0			
Unemployed, retired and others	138		164.16	2.0			
Household composition							
Person living alone	59	KWH Test	173.08	2.0	10.78 (4)	--	**0.029**
Couple without children	113		166.81	2.0			
Couple with children	104		193.67	2.0			
Household composed of flat-mates only (i.e. not a family home)	45		153.44	2.0			
Others	34		208.29	3.0			
No. of workers in hh							
None	64	JT Test	--	2.0	25,223.50	2.53	**0.011**
One	101		--	2.0			
Two	133		--	2.0			
Three or more	57		--	2.0			
No. of children < 18 years of age in hh							
None	249	JT Test	--	2.0	17,365.50	3.30	**0.001**
One	57		--	2.0			
Two or more	49		--	3.0			
No. of children < 13 years of age in hh							
None	274	JT Test	--	2.0	14,063.00	2.89	**0.004**
One	52		--	2.0			
Two or more	29		--	3.0			
Internet usage (past 7 days)							
Up to 15 hours	104	JT Test	--	2.0	25,800.00	2.42	**0.016**
16-25 hours	94		--	2.0			
26-35 hours	61		--	2.0			
More than 35 hours	96		--	2.0			
Time since first online shopping							
Up to 3 years	91	JT Test	--	2.0	23,563.50	3.35	**0.001**
4-6 years	103		--	2.0			
More than 6 years	161		--	2.0			
No. of cycles available in hh							
None	136	JT Test	--	2.0	22,480.50	1.86	**0.062**
One	88		--	2.0			
Two or more	131		--	2.0			
Frequency of missing deliveries							
Never	56	JT Test	--	2.0	22,564.50	2.04	**0.041**
Sometimes	184		--	2.0			
About half the time	55		--	2.0			
Most of the time or Always	60		--	3.0			

Note: hh – household; JT – Jonckheere-Terpstra; KWH – Kruskal-Wallis H; DV – Dependent variable; df – degrees of freedom; Z-value – Standardized Test Statistic; P-value – Asymptotic Significance (2-sided)

Appendix – 2: Results of the OL regression analysis

Frequency of online shopping during the past 12 months	**Estimate**	**Std. error**	**Wald chi-square**	**Odds ratio**	**P-value**
IFOS	-1.935	0.857	5.100	--	**0.024**
FOS	0.019	0.851	0.001	--	0.982
Age (years)					
18-29	1.000	0.355	7.926	2.72	**0.005**
30-39	1.194	0.363	10.792	3.30	**0.001**
40-49	1.265	0.407	9.663	3.54	**0.002**
50-59	0.375	0.355	1.113	1.45	0.291
60 or more	0	--	--	1.00	--
Household composition					
Person living alone	-1.848	0.849	4.734	0.16	**0.030**
Couple without children	-1.109	0.424	6.832	0.33	**0.009**
Couple with children	-0.649	0.442	2.152	0.52	0.142
Household composed of flat-mates only (i.e. not a family home)	-1.823	0.485	14.134	0.16	**<0.001**
Others	0	--	--	1.00	--
Household size					
One	1.813	0.845	4.598	6.13	**0.032**
Two	0.732	0.455	2.593	2.08	0.107
Three	0.026	0.401	0.004	1.03	0.948
Four	0.453	0.418	1.173	1.57	0.279
Five or more	0	--	--	1.00	--
Time since first online shopping					
Up to 3 years	-0.861	0.273	9.971	0.42	**0.002**
4-6 years	-0.495	0.263	3.540	0.61	**0.060**
More than 6 years	0	--	--	1.00	--
No. of cars available in hh					
None	-0.047	0.522	0.008	0.95	0.928
One	-1.100	0.346	10.086	0.33	**0.001**
Two	-0.662	0.307	4.637	0.52	**0.031**
Three or more	0	--	--	1.00	--
Frequency of missing deliveries					
Never	-0.700	0.391	3.200	0.50	**0.074**
Sometimes	-0.171	0.305	0.313	0.84	0.576
About half the time	-0.799	0.377	4.479	0.45	**0.034**
Most of the time or Always	0	--	--	1.00	--
Parcels being left unattended in the house compound is undesirable for me					
Strongly disagree	0.733	0.518	2.004	2.08	0.157
Disagree	0.843	0.405	4.318	2.32	**0.038**
Neutral	0.472	0.382	1.524	1.60	0.217
Agree	0.401	0.405	0.981	1.49	0.322
Strongly agree	0	--	--	1.00	--
Operating hours of post shops and pharmacies are not sufficient enough to facilitate collection of parcels					
Strongly disagree	-0.498	0.490	1.032	0.61	0.310
Disagree	-0.629	0.402	2.443	0.53	0.118
Neutral	-0.574	0.369	2.420	0.56	0.120
Agree	-0.748	0.364	4.225	0.47	**0.040**
Strongly agree	0	--	--	1.00	--
I am concerned that getting a parcel redelivered, adds to vehicular traffic and air pollution					
Strongly disagree	0.220	0.556	0.156	1.25	0.693
Disagree	0.913	0.542	2.838	2.49	**0.092**
Neutral	0.400	0.519	0.593	1.49	0.441
Agree	0.656	0.544	1.453	1.93	0.228
Strongly agree	0	--	--	1.00	--

Dependent variable (n)	1 = IFOS (85); 2 = FOS (135); 3 = VFOS (135)
-2 log-likelihood (intercept only model) = 765.105	-2 log-likelihood (final model) = 686.404
Chi-square statistic – Likelihood ratio tests = 78.700***	Degrees of freedom = 32
Pseudo R^2 (McFadden) = 0.103	

Note: hh – household; n – number of cases in each category