

# HOW MUCH CHOICE IS ENOUGH? COMPARING THE VALUE OF CHOICE FOR DIFFERENT ACTIVITIES

**Category:** *Collaboration between travel modes and networks*

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## ABSTRACT

A core principle of transport accessibility modelling is the concept that people value both destination convenience and choice. The value that people place on being able to access a particular destination is unique for different people and destination types, but generally reduces as the number of destinations that can already be reached increases.

The effect of diminishing marginal utility of destination choice is included in modern accessibility models, but has not been accurately quantified for New Zealand, and the different relationships for different destination types have not been thoroughly explored. In a collaboration between the University of Canterbury and Abley Transportation Consultants, travel behaviour information has been extracted from the New Zealand Household Travel Survey (NZHTS) and combined with community-contributed destinations data.

The varying value placed on accessing multiple destinations was then mathematically modelled using this dataset, distinguishing travel for all activity types contained within the NZHTS. The analysis combines data for three New Zealand cities: Christchurch (pre-earthquakes), Dunedin and Hamilton.

The results show that most people are happy with one of their closest choices for some types of destination, like primary schools and recreation. For others, like employment, tertiary medical/dental destinations, and tertiary education, a larger proportion of people will travel to a more distant option.

The results of this research take practitioners a step closer to answering the question “how much choice is enough?” with significant implications for understanding optimal supply of both land use and transportation.

## INTRODUCTION

Transportation accessibility is a fundamental component of transportation and urban planning that informs both on a macro-scale. Its importance is becoming more widely recognised in New Zealand; for example, it features in the title of the draft transport chapter of the Christchurch Central Recovery Plan, “An Accessible City”. Both New Zealand and Australia have seen recent uptakes in the research and application of accessibility modelling using geographical information systems (GIS), including Yigitcanlar, Sipe, Evans, and Pitot (2007), Espada and Luk (2011), Mavoa, Witten, McCreanor, and O'Sullivan (2012), and Abley and Halden (2013).

For many decades transport modelling has included measurement of accessibility in some form, though with an emphasis on mobility. Accessibility has been quantified as the sum of opportunities that can be reached, weighted by the time or cost of reaching that opportunity. However, there is an additional factor that needs to be considered: it is valuable to have some choice of competing destinations, such as different supermarkets or schools, but only up to a certain point. As the number of possible destinations increases, the value of each additional destination decreases. In economics this phenomenon is termed the law of diminishing marginal utility. Many models neglect this effect entirely, simply assuming that all destinations add to the overall accessibility if they can be travelled to, and relying on the impedance function to reduce the value of additional destinations because they are generally further away. Others use an intuitive but untested formula to reduce the value of additional destinations, or use high-level survey data to estimate the trend.

This research uses results from the New Zealand Household Travel Survey (NZHTS) to derive a mathematical function for each type of destination. The results show that most people are happy with one of their closest choices for some types of destination, while for others more people will travel to a more distant option.

## BACKGROUND

### Transportation Accessibility

Accessibility is a measure of the value of all the opportunities that can be reached from a particular location. Opportunities are valued destinations such as jobs, schools, shops and recreational facilities. Accessibility is the result of the combination of capability, opportunity and mobility (Abley & Halden, 2013):

- ‘Capability’ represents the ability of people to use the transportation network. For example, a bus with a low floor provides a capability for mobility-impaired to use public transport network, and being licensed to drive and having access to a vehicle provides a capability for people to use the road network.
- ‘Opportunity’ represents the availability of a land use activity or service. For example the presence of a supermarket provides an opportunity for shopping, and a school or college provides an opportunity for education.
- ‘Mobility’ represents the ease of moving through the various transportation networks. For example, speed limits and road congestion affect the level of mobility for vehicles. The amount of delay when crossing the street affects the level of mobility for pedestrians.

A location with high accessibility will have low travel times and travel costs to reach a range of destinations by multiple modes. High levels of accessibility are a product of both dense and/or mixed land uses and an efficient transport system.

### Accessibility Function Formulation

Accessibility of a location is typically formulated on the basis of a ‘gravity model’, which has been applied to motor vehicle travel for several decades with a focus on mobility (Iacono, Krizek, & El-Geneidy, 2010). A gravity model assigns higher value to destinations with many opportunities (‘mass’ in the gravity analogy), and reduces the value as travel time, distance or cost increases.

A typical formulation is:

$$A_i = \sum_j d(C_{ij})X_j$$

Where  
 A = accessibility score of origin i  
 j = potential destinations  
 d() = deterrence function weighting destinations by travel impedance  
 C<sub>ij</sub> = travel impedance from origin i to destination j  
 X<sub>j</sub> = opportunities at destination j

The deterrence function *d()* reduces the accessibility value of a destination as the travel costs *C<sub>ij</sub>* increase. For example, the deterrence function used by Espada and Luk (2011) is S-shaped (sigmoid) and uses travel time as its impedance basis; a short (<10 minute) trip has little deterrent effect, but there is a sharp drop-off in destination contribution to accessibility as travel times increase, levelling off at a near zero value for trips longer than 30 minutes. This function was based on several travel time utility surveys in the USA and Melbourne.

A more sophisticated accessibility formulation incorporates a “saturation function”, which accounts for the idea that it is possible to have enough destination choice, at which point choice is “saturated”. For example, accessibility formulations used by both Abley (2010),

$$A_i = \sum_j d(C_{ij})s(X_j),$$

and Espada & Luk (2011),

$$A_i = s\left(\sum_j d(C_{ij})X_j\right),$$

incorporate saturation functions, where symbols are defined as above, with the addition of:

s() = saturation function accounting for diminishing value of additional destination choice

The two formulations of the saturation function, *s()*, vary in that Abley (2010) treats impedance and destination saturation as independent contributors to accessibility, while Espada & Luk (2011) develops this to account for the travel impedance in reaching destinations before addressing destination choice saturation.

The saturation function applied by Abley (2010) is a ‘harmonic’ function, and has the following form:

$$s = \frac{X_j}{j}$$

Where: j = the rank of the destination (i.e. for closest destination j = 1)

The harmonic function has the advantage of being mathematically convenient, but has not been closely tested against real-world revealed preferences.

The the saturation function used by Espada & Luk (2011) has the following form:

$$s = \frac{1 - e^{-\varphi \sum_j d(C_{ij})X_j}}{1 + e^{-\varphi \sum_j d(C_{ij})X_j}}$$

Where:  $\varphi$  = a parameter  
 $\sum_j d(C_{ij})X_j$  = the impedance weighted sum of opportunities.

## **Supply, Demand and Marginal Value**

The economic principles of supply, demand and marginal value are long-established, extensively studied and covered in economics textbooks, e.g. Wicksteed (1910). These theories have been applied to transportation in the field of travel demand forecasting and in supply-side transportation infrastructure management (Federal Highway Administration (FHWA), 2009), with research emphasis in recent times on congestion pricing and multimodal transport economics (Victoria Transport Policy Institute, 2012).

The supply of destinations of various types is part of the geography of the built environment. Demand for choice of destinations has been studied in the context of economic competition, but research into how destination choice relates to accessibility is more limited.

## **METHOD**

The purpose of this research was to investigate the nature of the saturation function,  $s(X_j)$ , for trips to urban New Zealand destinations, using data extracted from the New Zealand Household Travel Survey (NZHTS) combined with community-contributed destinations data.

### **NZHTS description**

The NZHTS is an ongoing survey collected by the Ministry of Transport (MoT) with the purpose of monitoring and identifying ongoing travel trends. Participants are surveyed over a 48-hour period and information such as activity conducted at trip origin, activity conducted at trip destination, mode, duration and distance are recorded.

The database is presented in comma separated value (CSV) format, where each line represents one surveyed trip and contains all data for the trip, including the geocoded location of the destination. However, the database contains no information about routes travelled. Trip purposes, termed activities, are classified as described in Table 1. The dataset also contains details such that trip chains, the linking of multiple sub-trips, can be analysed.

### **Destinations data description**

Destinations data used for the analysis was extracted from Zenbu.co.nz, which maintains a community-contributed database of points of interest. Ideally, all destinations to which people travel would be represented within the dataset; however, the community-contributed nature of the data means that the level of quality is unknown. The data has been manually classified to match the derived functional activity classifications outlined in Table 1.

### **Trip chains**

A trip chain includes a stop on the way to another destination, and in this work has used the definition determined by McGuckin (2004), which defines the end of a trip chain as a stop that exceeds 30 minutes.

### **NZHTS data extraction**

Trip information was extracted from the NZHTS CSV dataset using a script written in the Python programming language. The script analyses the dataset sequentially, trip by trip, and builds chains from each sequence of trips. Trip purposes were converted from NZHTS activities to destination types for analysis as shown in Table 1. Work activities were aggregated into employment destinations, education activities were divided into different types of school and tertiary destinations, and social welfare was combined with personal business. Chains were discarded if the household made no trips either to or from the home, or any of the trip data used in the analysis was found to be invalid due to incomplete responses, missing required trip variables, or inaccurate

geocoding. Of the 349,000 trips contained in the database, 308,000 were usable. 40,000 trip chains were excluded due to containing no travel either to or from the home, and 400 contained invalid data.

**Table 1. NZHTS activity classifications and conversion to classifications used in the research**

NZHTS activity classification	Conversion	Study destination type
Home	<i>unchanged</i>	Home
Work: Main		
Work: Other	Combined into:	Employment
Work: Employers Business		
	Divided by age into:	
	<i>age &lt; 5</i>	Preschool
Education	$5 \leq \text{age} \leq 12$	Primary/Intermediate school
	$12 < \text{age} < 18$	Secondary school
	$18 < \text{age}$	Tertiary education
Shopping	<i>unchanged</i>	Shopping
Social welfare		
Personal business	Combined into:	Personal business
Medical/dental	<i>unchanged</i>	Medical/dental
Social visits	<i>unchanged</i>	Social visits
Recreational	<i>unchanged</i>	Recreational
Change mode	<i>excluded</i>	
Accompany someone	<i>excluded</i>	
Left country	<i>excluded</i>	
Other	<i>excluded</i>	
Overnight lodgings	<i>excluded</i>	

For each type of activity, there were three types of trip chain recorded: chains that start at home and terminate at the activity; chains that start at home, go to the activity, and return home; and chains that start at home, go to the activity, and end at a destination for some other activity.

The data is then stored within Geographical Information Systems (GIS) feature classes as matched pairs of points for every activity, specifying the origins and destinations of that trip. As a trip chain must start at home, and the chain is broken if more than 30 minutes is spent at any stop on the chain, for the purposes of this analysis each of the destinations reached on the chain is separately paired with the home origin. For example, consider a chain beginning at home, travelling to *shopping*, then to *personal business*, then to a different *shopping* destination, before returning home. This would create three origin-destination pairs: one for home-*shopping* travel, one for home-*personal business* travel, and a final pair for home-*shopping* travel.

As discussed later, this may have the effect of slightly over-estimating the value placed on reaching some destinations if they are only worth travelling to because they are clustered together with other destinations; however, major destinations like work and school remain unaffected, as do trips from work and school, because of the 30 minute stop limit on trip chains.

## Data analysis

For each activity, every origin-destination pair is analysed in conjunction with the Zenbu destinations data. The analysis is based upon Dijkstra's least-impedance path algorithm (Wise, 2002), which calculates the least-impedance route between two points for any arbitrary network impedance; the impedance variable used in this analysis is travel time. The algorithm has been extended to calculate the number of potential activity facilities forgone in selecting the destination. For example, a person may make a trip from home to a facility, but there may be two other equivalent facilities within a shorter travel time from the house than the selected shop, as shown in Figure 1. The original Dijkstra's algorithm finds the least-impedance route between an origin and destination by the following method:

1. analyse all network links connected to the origin,
2. select the link with the lowest impedance,
3. analyse all links connected to the origin and links connected to selected links,
4. select the link, or series of links, with the lowest cumulative impedance from the origin,
5. repeat 3 and 4 until the destination is located.

As the algorithm effectively works from the origin outward along the network until the destination is located the series of links which first includes the destination, and consequently terminates the calculation, must be the least-impedance path between the two. The updated algorithm keeps track of any other destinations for the same activity which are located before the destination. In the example shown in Figure 1 the updated algorithm would identify two facilities forgone prior to the destination being reached, meaning that for this trip the third facility was utilised. This process is repeated for each origin-destination pair within every activity classification.



**Figure 1. Hypothetical example of data used in this analysis, showing a trip where the third-closest facility was chosen.**

## Limitations

The classification scheme of the NZHTS includes both competing and non-competing destinations within the same category for some examples; for example, a book store and a clothing store are both classified as shopping within the NZHTS, but in reality they don't compete for the same trips, and one cannot satisfy the demand to access the other. In consequence, the results indicate the distribution of additional facilities accessed, for example "X percent of trips to shopping use up to the Y<sup>th</sup> potential facility", rather than stating that "people require Z supermarkets".

The quality of the Zenbu destinations data is unknown, both in terms of the coverage of actual destinations, and the accuracy of destination locations. This has the potential to significantly affect the output, although the data issues, and hence their effect upon the output, would be difficult to quantify.

Due to the nature of the analysis it is desirable to increase sample size as much as possible. Currently destinations have been classified for the cities of Christchurch (prior to the earthquakes), Hamilton and Dunedin, and hence the analysis amalgamates outputs from these three areas. However, there is a risk that different city forms, such as linear or radial, dense or spread out, and well or poorly served by public transport, may influence the output. In this instance it was assumed that the advantage of larger sample sizes outweighed the reduction in accuracy resulting from aggregating the data. However, it is a point of future research to analyse the effect of different urban forms.

## Model development

The output of the analysis was a distribution showing the percentage of trips passing a particular number of destinations, versus the number of destinations passed. 100% of trips pass at least 0 destinations, and the proportion eventually drops to 0% of trips passing the maximum number of destinations.

The output of the analysis for shopping is shown in Figure 2. This output was produced for all activity types specified in Table 1. For employment the x-axis variable indicates the number of employment opportunities passed, rather than the number of facilities. The outputs were then overlaid for comparison in Figure 3.

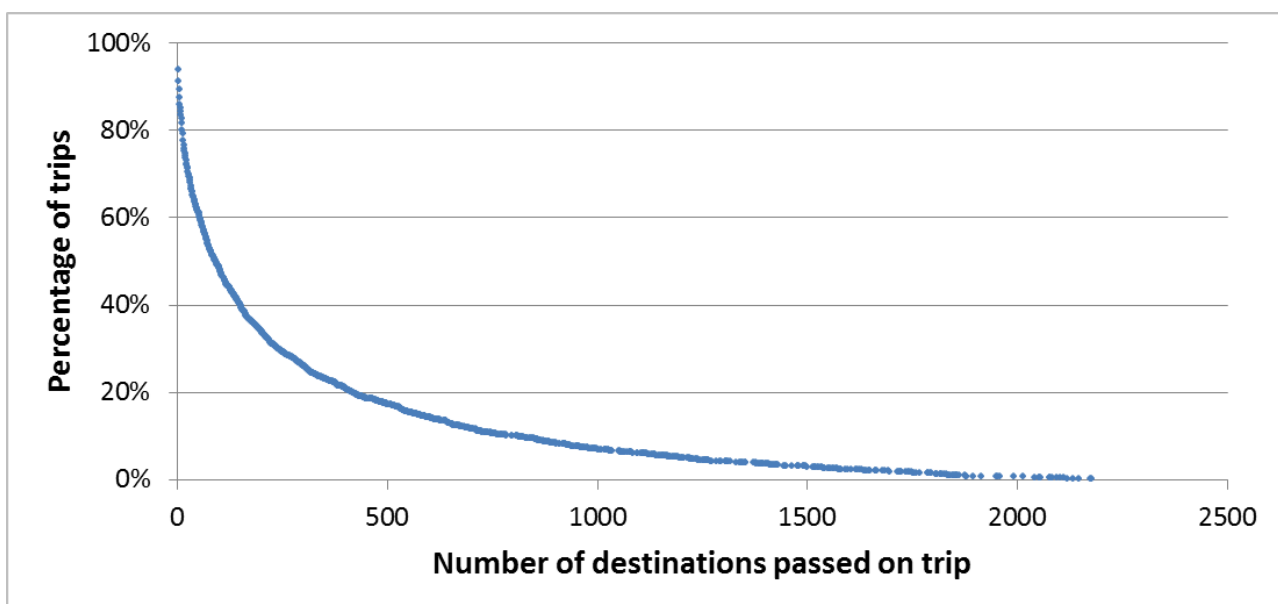


Figure 2. Output of analysis for *shopping* – combined result for Christchurch, Dunedin and Hamilton.

A series of curves were then fitted to each set of data with the aim of developing a mathematical model. Ideally one mathematical function would describe the observed data, for which one variable parameter might be used to differentiate between activities. Mathematical functions hypothesised to fit the data were:

the exponential function,  $y = e^{\lambda(x-1)}$ , where parameter  $\lambda$  has a negative value;

the logarithmic function,  $y = c \ln x + 1$ , where the parameter  $c$  has a negative value;

and the weighted inverse function,  $y = \frac{1}{p(x-1)+1}$ , where the parameter  $p$  has a positive value.

The logarithmic function was tested due to its good fit to the first half of the curves for some data – the best fit of all the functions tried in one case. However, it should be noted that, unlike the other

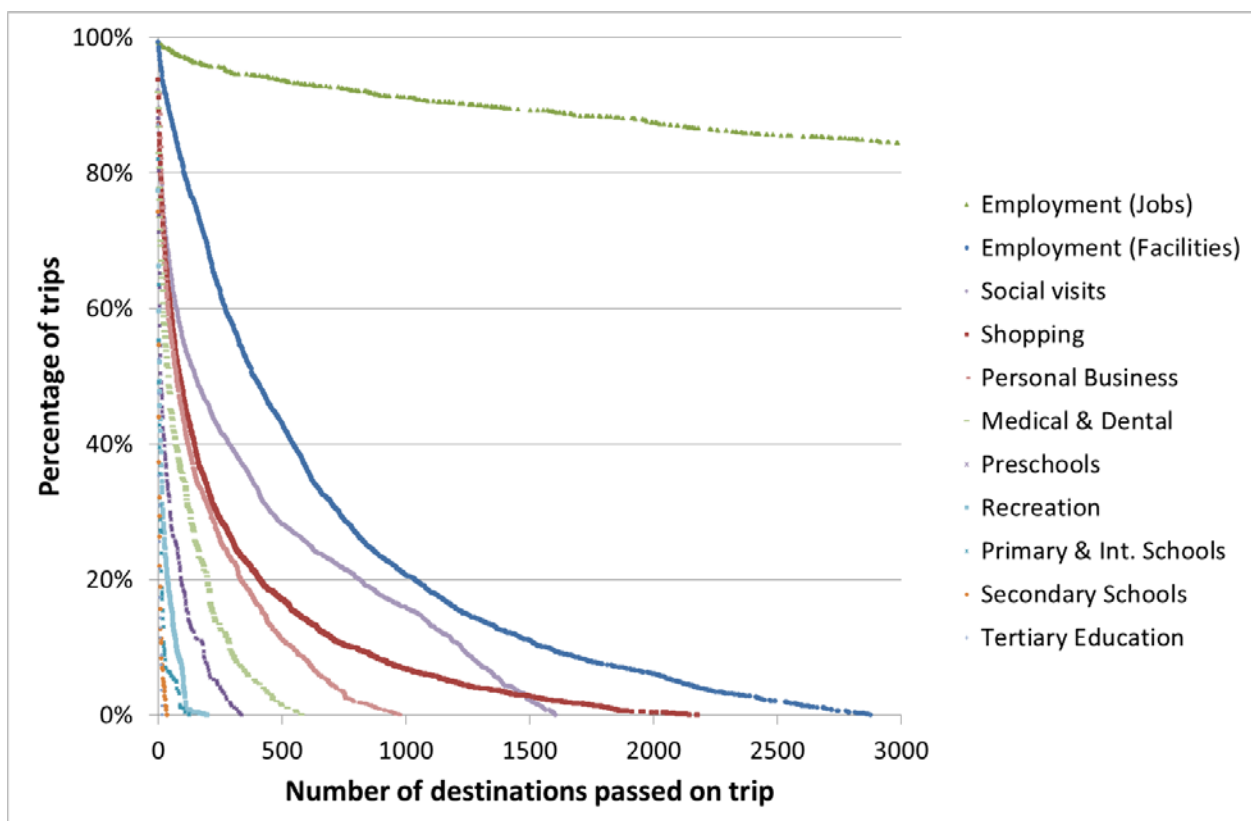
functions, it does not have an asymptote of zero and will produce negative  $y$  values for large  $x$  values. It was included in the analysis as over some ranges of  $x$  values, with certain curve parameters, it returns only positive  $y$  values.

A least squares analysis was used to determine the parameters of best fit for each curve for every activity. This was implemented through a data analysis script in the Python programming language, making use of the Scientific Python library. This least squares methodology uses an iterative method to determine best fit parameters, which often results in curves of significantly better fit than analytical methods, such as those used for trend line analysis by Microsoft Excel. This approach allows any arbitrary function to be tested against the data, with the best parameters fitted.

## RESULTS

### Comparison of activities

The results show that most people travel to a relatively close option for all activities, with a nonlinear long tail of progressively fewer trips that pass greater numbers of destinations, as shown in Figure 3. There are large differences between the number of destinations people pass for different types of activities.



**Figure 3. Comparison of different destination types showing proportion of trips passing different numbers of destinations.**

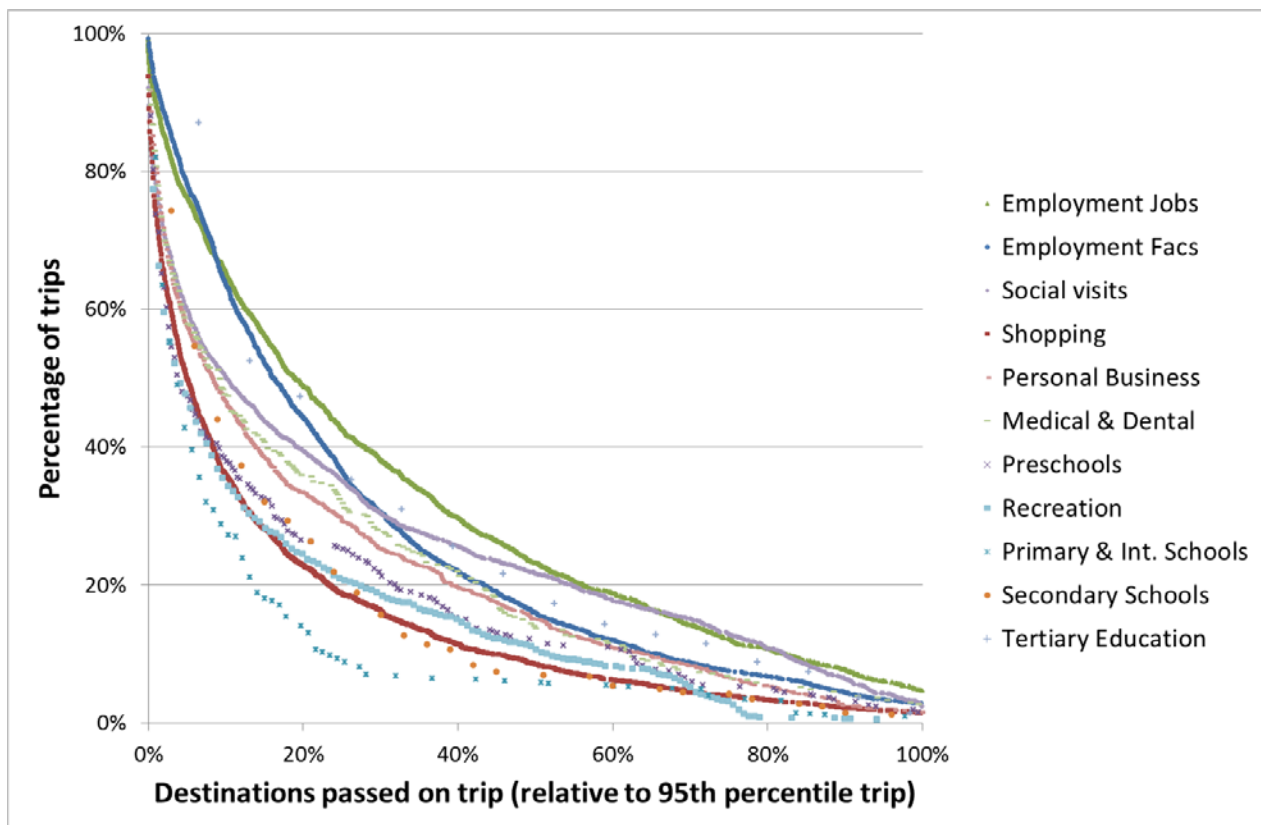
The results show that having access to 100 jobs is unlikely to satisfy a person's need for employment, as 98% of employment trips pass more jobs, while having high accessibility to 100 primary and intermediate schools is likely to be sufficient for most travellers, as only 1% of primary/intermediate school trips pass more schools.

Figure 3 shows that most people are willing to pass a very large number of jobs, social destinations and shops to get to their chosen destination, but will pass considerably fewer recreation opportunities or schools. This is in part because most *employment* and *social visits* are not actually competing alternatives, and because *shopping* aggregates non-competing types of shops. The



specific number of destinations that someone is willing to pass to get to their destination of choice appears to also depend upon the travel impedance to reach the destinations, which is a product of urban form: in an area with greater destination density or with higher transport mobility most trips are likely to pass more destinations.

To investigate the relationships for different destination types with less influence from these factors, the number of destinations passed on each trip was normalised by dividing by the number of destinations passed on the trip on which the 95<sup>th</sup> percentile number of destinations were passed. The normalised graph is shown in Figure 4.



**Figure 4. Normalised comparison of different destination types showing proportion of trips passing different numbers of destinations relative to the number of destinations passed on the 95<sup>th</sup> percentile trip.**

Significantly, the curves have not collapsed onto one line, although they have a reasonably similar decay form. There are evidently different relationships describing how many destinations travellers seek for different activities.

For all activities, the majority of trips are to a relatively close destination: 50% of trips pass fewer than 20% of the number of destinations passed on the 95<sup>th</sup> percentile trip. This was the relationship for employment trips. Trips to other destination types were even more weighted towards closer destinations: for example, 50% of shopping, primary/intermediate school and preschool trips passed fewer than 4% of the number of destinations passed on the 95<sup>th</sup> percentile trip. The full list of activity types is included in Table 2, showing the proportion of destinations that are passed by 80% and 50% of all trips.

**Table 2. Relative value of destination choice.**

Activity	Proportion of destinations reached by 80% of all trips (relative to 95 <sup>th</sup> percentile longest trip)	Proportion of destinations reached by half of all trips (relative to 95 <sup>th</sup> percentile longest trip)
Employment (opportunities)	56%	19%
Social visits	55%	10%
Tertiary education	49%	18%
Medical/dental	43%	9%
Personal business	39%	9%
Secondary school	26%	7%
Preschool	31%	4%
Recreational	26%	4%
Shopping	23%	5%
Primary/Intermediate school	13%	4%

### Fitting a model to the results

The analysis results indicate that it is possible to fit curves to the sampled data, and a variety of different curves present reasonable fit values ( $R^2 > 0.7$ ) for most activities, as shown in Table 2.

Interestingly, some destination data is fitted almost exactly by an exponential curve, some almost exactly by a logarithmic curve, and others by neither. Exponential and logarithmic curves are closely related, being the inverse of each other.

The weighted inverse function proves sufficiently versatile to provide a very good fit to all destination types.

**Table 3. Analysis results indicating coefficient of determination ( $R^2$ ) for model fits for activities, with best fit model underlined**

Activity	$R^2$ value			
	Harmonic	Exponential	Logarithmic	Weighted inverse
Tertiary education	0.77	<u>0.98</u>	0.97	0.93
Secondary school	0.83	0.97	0.87	<u>0.97</u>
Employment (opportunities)	-	0.97	0.49	<u>0.98</u>
Primary/Intermediate school	0.58	0.93	0.73	<u>0.99</u>
Medical/dental	<0	0.83	0.96	<u>0.96</u>
Shopping	<0	0.82	0.95	<u>0.98</u>
Personal business	<0	0.80	0.94	<u>0.96</u>
Social visits	<0	0.74	0.87	<u>0.93</u>
Recreational	<0	0.69	0.92	<u>0.95</u>
Preschool	<0	0.69	<u>0.99</u>	0.94

The weighted inverse function provides the best fit for all but two activities. Travel to *preschools* is best fit by the logarithmic function and *tertiary education* is best fit by the exponential function. However, in both these cases the weighted inverse function still provides a reasonable fit ( $R^2 > 0.7$ ).

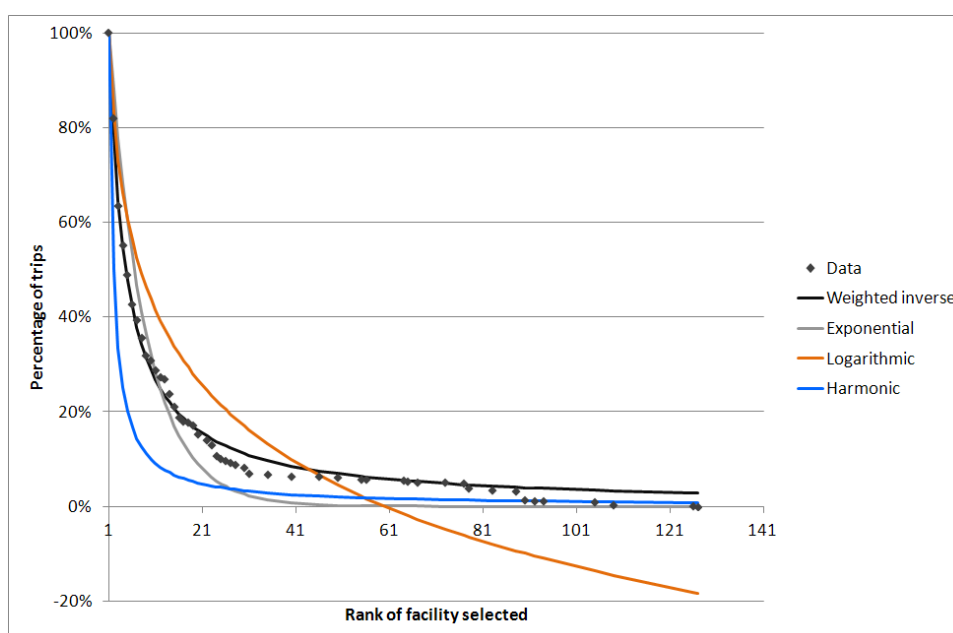
The harmonic function is included for comparison, although the  $R^2$  fit is  $< 0$  for many activities, particularly those with high numbers of non-competing destinations.

The weighted inverse function parameter values for the curve fitted for each activity are given in Table 3. Larger  $p$ -values indicate a larger proportion of trips use the closest facilities, and hence additional destinations have lower value. Activities for which greater percentages of trips are to more distant destinations, and for which there are large numbers of non-competing destinations, such as *shopping* and *social visits*, have lower  $p$ -values.

**Table 4. Parameter values for the fitted curves of percentage of trips vs number of destinations passed**

Activity	Exponential ( $\lambda$ )	Logarithmic ( $c$ )	Weighted inverse ( $p$ )
Employment (opportunities)	$-2.71 \times 10^{-5}$	-0.0566	$4.78 \times 10^{-5}$
Preschool	-0.029	-0.176	0.059
Primary/Intermediate school	-0.127	-0.244	0.274
Secondary school	-0.214	-0.313	0.485
Tertiary education	-0.233	-0.364	0.488
Medical/dental	-0.012	-0.150	0.024
Personal business	-0.007	-0.137	0.014
Recreational	-0.054	-0.210	0.129
Shopping	-0.005	-0.131	0.011
Social visits	-0.003	-0.118	0.006

The weighted inverse function fits the *primary/intermediate school* activity best, shown in Figure 5.



**Figure 5. Data and fitted curves for primary/intermediate schools.**

## DISCUSSION AND FUTURE WORK

These results show that people are more willing to accept their closest option for destinations like preschools, primary/intermediate schools, shopping and recreation, but require access to a greater proportion of the available options for destinations like employment, social visits and tertiary education. This is an intuitive result, and it is valuable to be able to quantify the effect.

The activity categories studied appear to have stratified into three types of destination, clearly visible in Table 2:

- Supplied activities: *employment* and *social visits* both depend on the traveller in some way, and most of the available destinations are not substitutable for the desired destination.
- Differentiated consumed activities: *tertiary education*, *medical/dental*, *personal business*, and *secondary school* activities have options that broadly compete and serve the same purpose; however, they have quite different levels of quality and it would appear that people are willing to travel further to reach their preferred destination, rather than settling for a close option: they place a greater value on destination choice.
- Substitutable or competing consumed activities: *preschool*, *recreation*, *shopping*, and *primary/intermediate schools* were the most weighted toward relatively short trips, with most people opting for a close option. This suggests having a wide range of options for these activities is less important.

Activities were separated into 'supplied' and 'consumed' by Abley and Halden (2013), though the only supplied activity identified was *employment*; this work supports the distinction and is able to add *social visits* to supplied activities due to the more detailed survey data.

Further research could investigate disaggregating activity types as far as possible so that substitutable or competing subsets may emerge from categories that are currently differentiated; *personal business* and *shopping* in particular are likely to be divisible in this way. Some non-competing effect will remain due to data limitations, requiring calibration of the models to account for this.

It would be valuable to attempt to weight the value of each destination by the size of opportunity it offers; for example, Espada and Luk (2011) used the number of pupils enrolled as a measure of school size. This concept could be extended to quantify the opportunity provided by destinations for retail, medical facilities, recreation and other activity types but will require relatively extensive data collection and processing.

A useful comparison could be made by fitting the saturation function formulation used by Espada and Luk (2011) to the NZHTS data, and comparing the resulting parameters to those determined in their paper by calibration against Australian travel survey data.

This analysis methodology could be extended by future research to investigate differences in the value of destination choice associated with:

- *Urban form*. NZHTS trip chain information for three cities, Christchurch, Dunedin and Hamilton, was combined in the output, from which the models were built. Future work will analyse data for the three cities separately, as the urban form may significantly affect the number of facilities forgone when selecting a destination. Additionally, changes to the distribution of housing and activities in Christchurch could provide an interesting case study on whether people now travel further, accept a reduced range of choice or, as would be predicted by modelling the supply and demand functions for destination choice, a compromise between these.
- *Work-based and home-based travel differences*. People may be more inclined to go to their closest option from work because the constraints on their time are greater.
- *Demographic differences*. The saturation and impedance functions are subjective and unique to each person – this study uses averages. The impedance and saturation functions

are likely to vary in opposite ways as an increasing value of time may be associated with an increasing value of destination choice.

- *Mode of travel.* This is likely to be particularly significant for trip chaining and length. A higher proportion of car trips may be single-purpose and longer, public transport trips may favour destination clusters such as malls, cycle travel may favour trip chaining to destinations on people's work-home commute route, and walking may be dominated by trips to the closest destination, whether from home or work. The majority of trip data in the NZHTS for car travel, which could constrain multimodal analysis.

A plot of the average cost of reaching each extra destination choice, relative to the number of destinations actually passed on a trip, Figure 5, bears an intriguing similarity to the traditional economic demand curve plot of unit price versus quantity demanded, Figure 6. Without considerably more detailed data it is not possible to find the marginal price at which further travel ceases, only the average price.

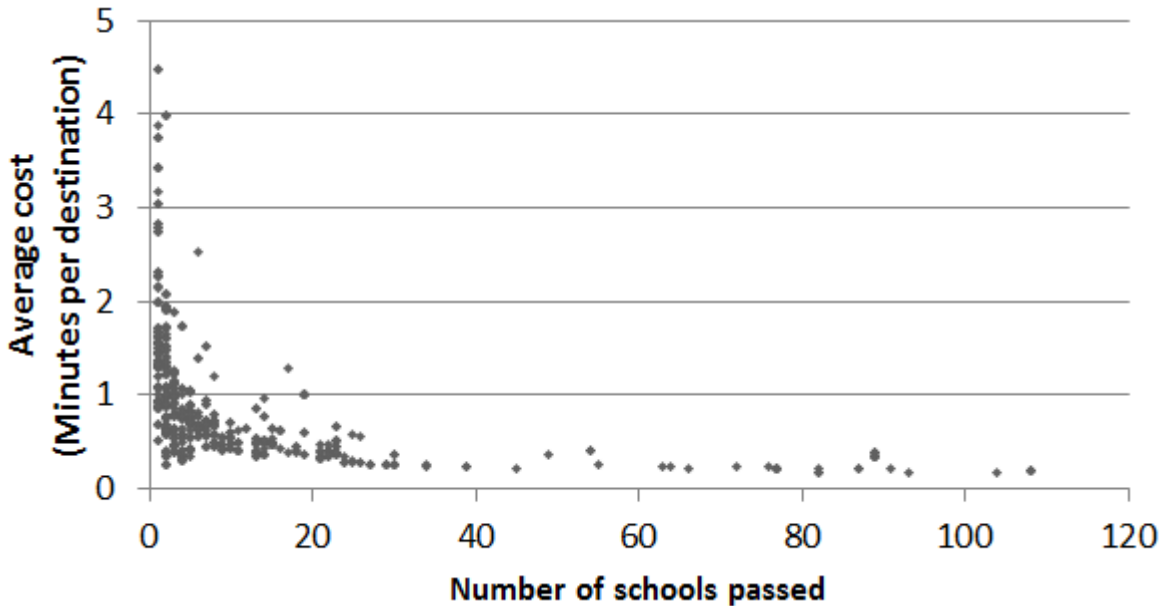


Figure 5. Average cost per destination versus total destinations passed on trip, for primary/intermediate schools.

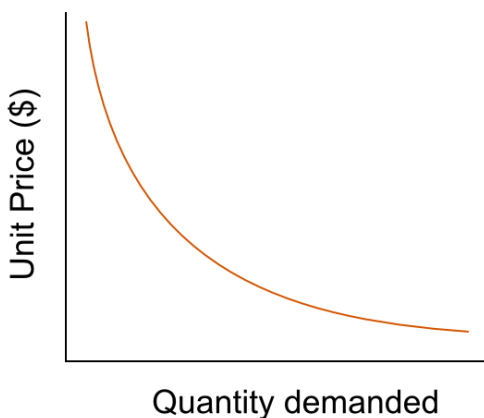


Figure 6. Typical theoretical demand curve.

Future research could further investigate the demand curves for destination choice for different types of activity, and determine supply curves showing the rate at which destinations can be reached with further travel from a specific origin, using technology like GIS.

## CONCLUSION

Destination choice is valuable to travellers, with very few people using their very closest option for any given activity. However, for all types of activity covered in the New Zealand Household Travel Survey, at least half of all travellers select one of their closest 20% of destinations. The other half of travellers place sufficient value on being able to choose from the remaining 80% of destinations that they are willing to travel further to reach them. Trip lengths were normalised against the 95<sup>th</sup> percentile trip length to account for different numbers of available destinations for different activities.

This research has examined how existing accessibility models treat the value of destination choice and the cost of travel impedance. Destination choice value functions, modelling the 'saturation' of demand with increasing choice, have been developed for the New Zealand data.

This has enabled interesting comparisons to be made between the value of choice for different types of destination. Three key groups emerged: first, destinations where the traveller is integral to the activity so travellers place a high value on accessing their destination of choice: employment and social visits; second, destinations that are significantly differentiated to travellers so have a high value of choice, such as different tertiary education institutions, different medical/dental care options, and different types of shopping; and thirdly where destinations are substitutable or the value of choice is lower, such as recreation and primary/intermediate schools.

In the process some limitations to this analysis were found. Two particular aspects of destination choice that were not modelled due to absence of data were the magnitude of opportunity that different destinations provide, with some being considerably larger than others, and the effect of aspects of urban form like clusters of different destinations, which can attract a chain of trips even if their individual value would not justify the distance travelled. Modelling travel choice value for different demographic groups, travel modes, and from different types of origin could also provide useful insight for transport and land use planning.

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