Household Vehicle Ownership: Does Urban Structure Matter?

Ali. Soltani[1] Sekhar Somenahalli[2]
[1] University of South Australia, Adelaide, SA, Australia
[2] University of South Australia, Adelaide, SA, Australia

1 Introduction

According to the ECMC (2001) report - a survey amongst cities throughout the world - in terms of the relationship between population density and the subsequent car ownership rate, Australia was found to have a relatively low density and a high car ownership rate. The central point of this paper is whether there is a significant association between the macro-scale attributes of the urban area where a householder has chosen to live and the number of vehicles owned by the household. Vehicle ownership has mostly been considered as an explanatory variable in travel demand systems. On the other hand, vehicle ownership has been investigated as a function of household preference and socio-economics. A little systematic effort, in fact, has been made to treat vehicle ownership within a broader framework of household choice regarding housing location, workplace, and travel patterns (Waddell 2001). Therefore, it is still unclear how land uses patterns impact upon the level of vehicle ownership although a few studies tried to explain the relationship (Holtzclaw et al. 1994; Schimek 1996). The hypothesis – taken from New Urbanism ideas- is that areas with higher density, better access to public services and more opportunity to non-motorized modes of travel are associated with lower auto-dependency and lower rates of vehicle ownership. In this study, metropolitan Adelaide, in South Australia is considered as a case study because it is an example of car-dependent areas.

2 Literature review

2.1 Theoretical base

Car-dependency is a significant challenge for achieving sustainable cities in Australia. Car-dependency has several human and environmental impacts. It increases total mobility, vehicle traffic and associated costs. It increases the importance of automobile travel and reduces the importance of other modes. In a car dependent community virtually every adult needs a personal vehicle. Car-dependency reduces the range of solutions that can be used to address problems such as traffic congestion, road and parking facility costs, crashes and pollution (Victoria Transport Policy Institute 2005).

Policies should be aimed at reducing the reliance on private vehicle travelling. *Smart Growth* is a general term for policies that integrate transportation and land use decisions, for example by encouraging more compact, mixed-use development within existing urban areas, and discouraging dispersed, automobile dependent development at the urban fringe (Ewing 1996). Smart Growth can help create more accessible Land use patterns, improve transport, create more liveable communities, and reduce public service costs. American New Urbanism movement supports development of a more connected street network, often using a modified grid pattern. This provides multiple routes and more direct travel between destinations compared with a disconnected street network with many dead-end roads that result in more circuitous routes, and direct traffic onto a few roadways. Increased street connectivity has been showed to reduce per capita vehicle travel, and reduce traffic volumes on major roads (Handy et al 2004). One expectation of these reformist ideas is to reduce the level of car dependency by providing better accessibility and more travel choices. It seems that car dependency can be regarded as the result of a cycle that increases vehicle travel, reduces non-automobile travel options and reduces land use accessibility (Victoria Transport Policy Institute 2005). Reversing these factors can help create more balanced transport systems.

2.2 Empirical studies

As highlighted by Smart Growth and New Urbanism movements, some aspects of an urban structure might be important in influencing car ownership:

- Density: The early study by Newman and Kenworthy (1989) clarified that the low density areas under 30 persons/ha generate automobile dependence due to a combination of factors including greater distances to travel and little option to walk or use public transport. So, for those areas where densities are over 40/ha, the public transport is a strong travel option and hence the automobile is not a high priority option in such urban environment. Pushkarev et al (1982) in their study of American cities suggested that the higher density is associated with the lower ownership and the lower use of automobiles. The households located in high density areas own fewer cars than those in the low density areas (Hess and Ong 2003). The lower level of car ownership in higher density areas is probably the result of greater vehicle costs such as parking costs.
- Land use diversity: The other urban variable, which is important, is the mix of land use. Mixed land uses provide more transport options. A more accessible land use pattern means that less mobility (physical travel) is needed to reach goods, services and activities. Lynch (1986) explained that Canberra, Australia is a place in which shops are several kilometres or more from most homes and workers must travel 8 kilometres to workplaces. The open spaces are located in quite far-off places; without proper access. Then he concluded that such dispersed distribution of activities result in wasted land and inevitable problems of travelling and social cohesion. On the other hand, increasing transportation accessibility through transit -oriented development (TOD) has the potential to increase the share of trips made by (transit ?), in addition to influencing car ownership levels. Also, clustering different uses such as shopping, offices and retailing would help to encourage more trips done by walking and public transportation. Such development certainly could decline the level of car ownership and car use. Cervero (1996) found a significant amount of elasticity between built environments and commuting choices in 11 large U.S. Metropolitan areas. The neighbourhoods with mixed land uses tended to reduce vehicle ownership rates and were associated with shorter commutes, controlling for socio-economic characteristics. Kockelman (1997) analysed the travel data in the San Francisco region and found that a doubling in accessibility results in a 7.5% decrease in the number of vehicles owned by a household, when controlling for other urban and household factors.
- Network design: street network design can also affect travel behaviour in several ways. A connected road network provides better accessibility than a conventional hierarchical road network with a large portion of dead-end streets (Handy et al 2004). Increased connectivity can reduce vehicle travel by reducing travel distances between destinations and by improving walking and cycling conditions, particularly where paths provide shortcuts. Pedestrian environment can also impact upon vehicle ownership. According to the study of 1000 friends by Oregon (1996), pedestrian environments were found to be important in estimating the number of vehicles owned per household. Similarly, in a logit model presented for vehicle ownership for the Chicago area, the pedestrian environment and car work trip modal share were found to be statistically significant in forecasting vehicle ownership rates. Less than 40% of these households in urban areas have two or more vehicles while more than 90% in suburban areas have two or more vehicles (Eash 1996).

It can be concluded from these background studies that some features of the urban structure can be significant factors in affecting vehicle ownership in some cases. On the other hand, the findings of such studies have remained ambiguous in terms of the amount and direction of the effect of urban factors for different study areas.

3 Methodological approach

It is assumed that the probability that a household owns a vehicle is a function of several factors including socio-economics and urban structure elements (Holtzclaw et al. 1994; Hess and Ong 2003). Therefore, the average vehicle number per household is primarily a function of neighbourhood density, income, household size and the availability of public transport. A model for an examination of the probability of vehicle ownership can take the following form:

$$\text{Vehicle ownership} = f\,(SE, US). \qquad (1)$$

Such a model involves not only a determination of how land use pattern relates to the level of vehicle ownership, but also how they relate to the other factors of influence. In this formula, SE is a vector of socio-economics such as household size, household type, household income, and dwelling structures. For instance, increasing the household size raises the probability of owning more vehicles because of the higher demand of workers or their children for vehicle use. In addition, increasing household income will increase the probability that households will own a greater number of vehicles. The second group of important factors is indicated by the ‘US’ vector and includes urban structure characteristics such as density, land use mix, distance to workplace and design features. The aim of this study is to discover the role of these factors.

3.1 Study data and methodology

A database was created using different datasets including the 1999 Metropolitan Adelaide Household Travel Survey (MAHTS99), Journey to Work (JTW) Transportation Area Zones (TAZ) Survey and the South Australian Digital Cadastral Data Base (DCDB). In the database, each household was considered as one data record, which totalled to 5760 households for metropolitan Adelaide, South Australia. The study area covers whole of metropolitan Adelaide area zones which were used in the JTW Survey (Figure 1).

The 1999 Adelaide Household Travel Survey was conducted over two days. The respondent households (about 2% of Households) were randomly selected across the Adelaide metropolitan area. Interviews were then undertaken for the selected households in the survey. All the members of each household were asked to provide details of all their travel activities made over two consecutive days, including their travel destinations, travel starting times, the purpose of travel, and socio-demographic information.

Figure 1 depicts the overall image of metropolitan Adelaide and the geographical distribution of population (in persons per hectare) and vehicle ownership (in vehicles per household) within metropolitan Adelaide. This figure shows the imbalanced physical development of Adelaide. As shown in the Figure, the lower population density outer suburbs - especially in the eastern side and northern wing- have higher vehicle ownership levels. The average vehicle ownership for these areas ranges from 1.8 to 2.7 vehicles per household. On the other hand, centrally located older suburbs have higher population density but lower level of vehicle ownership.

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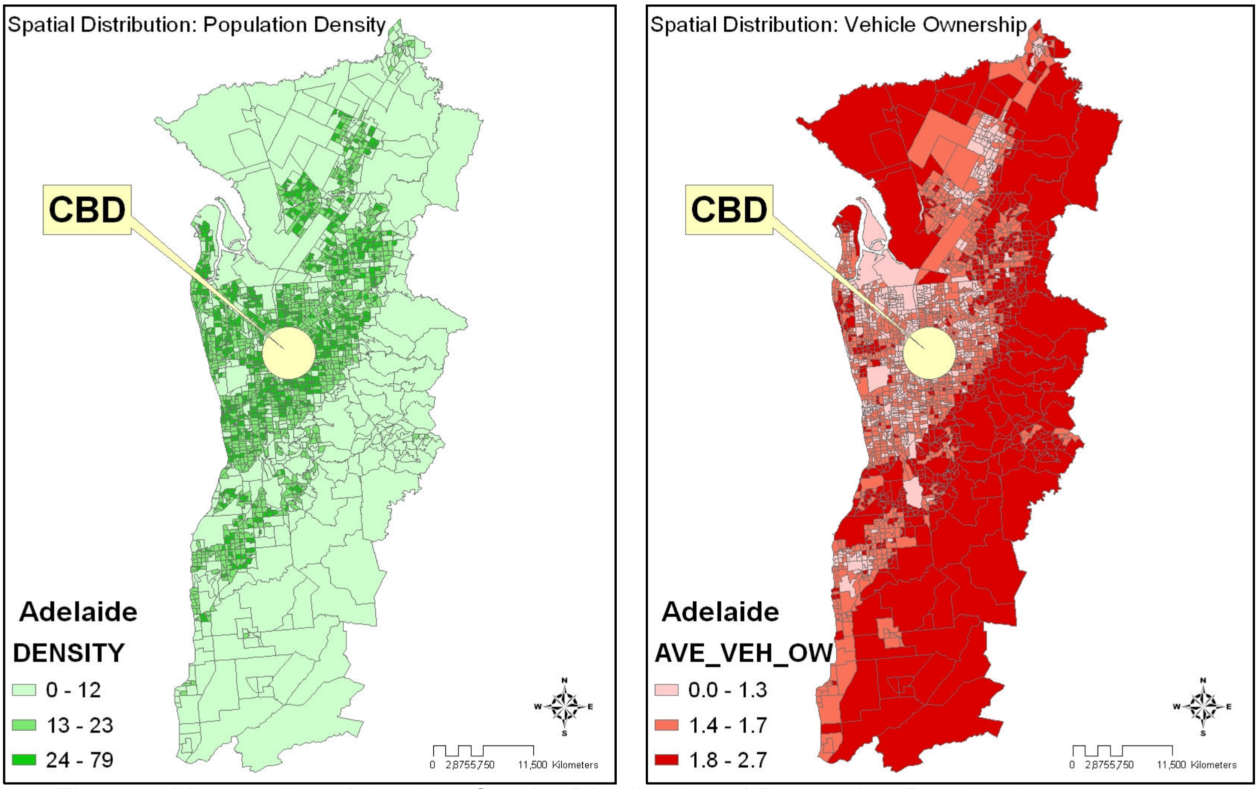

Figure 1 Metropolitan Adelaide: Spatial Distribution of Population Density (person per hectare) and Vehicle Ownership (vehicle per household) in Metropolitan Adelaide (Source ABS 2001).

3.2 Modelling

The multinomial logistic regressions were applied to model the decision to own one, two, three or more vehicles as the dependent variable. Logistic regression applies maximum likelihood estimation after transforming the dependent into a logit variable. In this way, logistic regression estimates the probability of a certain event occurring. Parameter estimation is performed through an iterative maximum-likelihood algorithm. Logit coefficients are used for interpreting. Logits are the natural log of the odds. They are used in the logistic regression equation to estimate (predict) the log odds that the dependent equals its highest/last value. The logistic regression calculates the changes in the log odds of the dependent, not the changes in the dependent itself. Multinomial logistic regression is an extension of binary logistic regression that allows the simultaneous comparison of more than one contrast. That is the log odds of three or more contrasts are estimated simultaneously (Hosmer and Lemeshow 2000).

It is assumed that vehicle ownership decisions are an expression of preferences, and vehicle ownership can be predicted if the utility function and all of the relevant factors are known. This method has been verified as a reasonable methodology (Meurs 1993; Bhat and Kopplman 1993; Hocherman et al. 1983).

> *"As a general guideline, auto ownership modelling must be pursued using the unordered-response class of models (such as multinomial logit models or the multinomial probit models)." (Bhat et al. 1998 page 74).*

Therefore it is preferred to use multinomial logit rather than ordinary least squares (OLS) regression. A multinomial logit model is expressed as (Ben-Akiva and Lerman 1985):

$$P_{ik} = \frac{e^{Z_{ik}}}{\sum_k e^{Z_{ik}}} \qquad (2)$$

where P_{ik} is the probability that the i^{th} case falls in category k. Z_{ik} is the value of the k^{th} unobserved variable for the i^{th} case. For a dependent variable with k categories, consider the existence of k unobserved continuous variables $Z_1, Z_2, \ldots Z_k$ each of which can be thought of as the "propensity toward" a category. In the case of a vehicle ownership, Z_k represents a household's propensity toward selecting the k^{th} vehicle, with larger values of Z_k corresponding to greater probabilities of choosing that vehicle (assuming all other Z's remain the same).

Mathematically, the relationship between the Z's and the probability of a particular outcome is described in this formula.

$$Z_{ik} = b_{k0} + b_{k1} x_{i1} + \ldots + b_{kj} x_{ij} \tag{3}$$

where x_{ij} is the value of the j^{th} predictor for the i^{th} case. b_{kj} is the j^{th} coefficient for the k^{th} unobserved variable and j is the number of predictors. Z_k is also assumed to be linearly related to the predictors. Since Z_k is unobserved, the predictors must be related to the probability of interest by substituting for Z_k. As it stands, if a constant is added to each Z, then the outcome probability is unchanged. This is the problem of non-identifiably. To solve this problem, Z_k is (arbitrarily) set to 0. The k^{th} category is called the reference category, because all parameters in the model are interpreted in reference to it.

In the model developed for this study, *owning one car* is chosen as reference category because it is the most frequent choice. The distribution of data shows that only less than 9.5% of Adelaide's households have no vehicles. About 40% of households have one vehicle, whereas 37% of the householders have two vehicles. And 13% have three or more vehicles. Explanatory variables were selected from the available datasets to represent each of the factors outlined in the conceptual model. They were based on the hypothesized relationship between the characteristics of urban structure and vehicle ownership. The variables considered in the analysis are listed in Table 1. The vehicle ownership models in this study use the household as the decision-making unit. It is structured more behaviourally compared to the aggregate vehicle ownership models (which model vehicle ownership at the zonal, regional, or national level).

A descriptive statistics including minimum, maximum, mean, standard deviation and frequency of the variables included in the modelling are summarized in Table 2. The variables were included in modelling if they showed a significant association with the dependent variable in the preliminary correlation analysis (the regressors also were checked for collinearity bias). The following logit models as summarized in Table 3 indicate that the probability of a household owning a vehicle is affected by different factors. They also determine the magnitude and direction of the effect of the factors predicting the vehicle ownership of the household.

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Table 1 Variable Description.

Variable	Description
Dwelling density	Number of dwellings per area (units/acre).
Land Use Mix (LUM)	Mean entropy for land use categories within a zone (CCD) LUM for each zone, computed as: $\{\sum_k [\sum_j P_{jk} \mathrm{Ln}(p_{jk})]/\mathrm{Ln}(j)\}/k$, where: P_{jk} = proportion of land use category j within a zone; j = number of land use categories; and k = number of actively developed hectares in zone. The mean LUM ranges between 0(where in all land uses area of a single type) and 1(where in developed area is evenly distributed among all land use categories) this index suitably indicates the diversity of an urban area (Cervero and Kockleman 1997). The number of seven categories considered for this study: residential; commercial; recreational; industrial; governmental; community services and open spaces. The source used here was DCDB land use map. Dummy variable For LUM > 0.50 [LUM=1]; for LUM < 0.50 [LUM=0].
Grid street network	The layout of street network for each zone observed. If more than 50 per cent of the network built as grid it is called Grid network. Dummy variable for Grid network [Grid street =1]; for other [Grid street =0].
Distance to Adelaide CBD	The distance between the centre of each zone and Adelaide's CBD – Victoria Square- was measured. The measure was based on the least cost path following metropolitan roads network using Network Analyst extension of ArcView GIS.
Jobs housing balance	Ratio of total jobs to total household workers.
Public transport coverage	The percentage of transit-supportive area covered for each zone. Covered area is the area within 0.4km of local bus route, where pedestrian connections to transit area available from the surrounding area.
Home structure	Dummy variable for the household living in a separate house [Home Structure=1]; for semi-detached, row or terrace house, townhouse and flat, unit or apartments [Home Structure=0].
Household living with children	Dummy variable for householders as Family or single adult living with children [Household Type=]; for others [Household Type =0].
Person living alone	Dummy variable for householders as Person living alone [Person living alone=1]; for others [Person living alone=0].
Number of members	Mean household size (no. of members).
Household income	Mean income (year) of the of household (the summation of all the personal income within each household).
Vehicle ownership	Discrete values for the number of available vehicles per household For owning no vehicle : No of Vehicle =0; For owning one vehicle: No of Vehicle =1;For owning two vehicles: No of Vehicle =2; For owning three or more vehicles: No of Vehicle =3

Table 2 Descriptive Statistics for Included Variables.

Variable	Minimum	Maximum	Mean	Std. Dev.	No. Case
Distance to CBD (km)	.310	52.136	14.812	9.126	5760
Dwelling Density (unit/acre)	.020	19.410	6.939	3.530	5760
Grid Street	0	1	.47	.499	5760
Income ($AUS per year)	1040	195000	41605	31198	5760
Jobs Housing Balance	.025	3.10	.232	.260	5760
Family has children	0	1	.16	.369	5760
Person living alone	0	1	.25	.432	5760
Land use mix (LUM)	0	1	.48	.500	5760
No of members	0	8	2.48	1.303	5760
No of vehicles	0	3	1.54	.839	5760
Living in a separated house	0	1	.77	.423	5760
Public transport coverage	.28	100.00	80.79	25.11	5760

(Source: MAHTS99)

4 Findings

The results achieved by the modelling process can be summarized as follows (see Table 3):

- From the ρ^2 value - informal goodness of fit index- we see that the model fits the data properly. The comparison of the Log Likelihood values for no coefficients and the model included coefficients shows the importance of explanatory variables in explaining the variation. Some other urban variables such as distance to workplace and accessibility to public services can be entered to test their importance in influencing vehicle ownership. Also inclusion of more socio-economics factors would be useful to increase the power of the model.
- In all three models, the following variables found to be important as statistical determinants of vehicle ownership: household income; family type; home structure and dwelling density.
- Having higher income increases the likelihood of the owning two; three or more vehicles with respect to owning one vehicle. The effect of household income is stronger for owning three or more vehicles than for owning two vehicles. As expected this coefficient has negative sign for the category of owning zero vehicles compared to the category with one vehicle.
- Being in a family type as *living alone* decreases the probability of owning two or three or more vehicles for a household and increases the probability of owning zero cars compared to the referent category (owning one car).
- For those who live in separated houses, the probability of having more than one vehicle increases. One reason could be that for those householders living in separate houses, more parking might be available than for other people living in other dwelling structures, thus increasing the likelihood of vehicle ownership. For those owning no vehicles, the effect of dwelling of separated house is negatively significant.
- Households with more members are more likely to own more vehicles because of higher mobility requirement (Bhat and Koppelman 1993). Additional household members are likely to increase the number of workers in the household, which is correlated with higher vehicle ownership. One may argue that the increase in household size may imply greater essentials such as food, clothing and housing, thus reduces the amount of financial resources for expenditures on cars (Lerman and Ben-Akiva 1975). But in this study, the result can be attributed to higher demand because of more mobility needs.

- The presence of children in a household increases the probability of vehicle ownership for householders. This effect reflects the positive impact of children due to higher mobility requirements such as driving them to school (Hocherman et al. 1983).

Table 3: Parameter Estimates.

No of Vehicle	Variable	B	Std. Error	t-statistics	Exp(B)
0	**Intercept**	-0.522	0.438	-1.192	
	Income	-0.062	0.005	-12.400	0.940
	Dwelling density	0.058	0.02	2.900	1.060
	Separate house	-0.606	0.107	-5.664	0.546
	Living alone	0.661	0.192	3.443	1.937
2	**Intercept**	-3.563	0.251	-14.195	
	Income	0.029	0.002	14.500	1.029
	No of members	0.458	0.044	10.409	1.581
	Dwelling density	-0.022	0.01	-2.200	0.978
	Jobs-housing balance	-0.32	0.151	-2.119	0.726
	Separate house	0.696	0.097	7.175	2.006
	Living alone	-1.278	0.136	-9.397	0.279
	have kids	0.549	0.111	4.946	1.731
3+	**Intercept**	-5.92	0.39	-15.179	
	Distance to CBD	0.018	0.007	2.571	1.018
	Income	0.041	0.002	20.500	1.042
	No of members	0.728	0.053	13.736	2.071
	Dwelling density	-0.031	0.014	-2.214	0.969
	Separate house	0.893	0.169	5.284	2.442
	Living alone	-0.978	0.274	-3.569	0.376

Not: Coefficients in the table are significant with 95% confidence. No. of Vehicle=1 is the reference category.

Model Summary:
Chi-Square (24) = 3515.500
Number of cases = 5760
-2 Log Likelihood (intercept only) = 13623.555
-2 Log Likelihood (final) = 6021.475
ρ^2 = 0.562

- The analysis also showed that some of the variables related to urban structure including jobs-housing balance, dwelling density, and distance from CBD are significant in explaining the level of vehicle ownership in some cases: density has significant negative association with owning three or more vehicles. In contrast, living in an area with higher (dwelling) density resulted in less likely to own a vehicle. This may be due to the limitations of parking or due to traffic overcrowding. Or since denser areas are usually associated with better public transport services as well as accommodating different social groups which all together make a denser area feasible for non-automobile travel activities thus decreasing car ownership level (Kitamura et al. 1997).
- The indicator of jobs-housing balance is significantly associated in explaining the owning of two vehicles for the household. The higher the value of this index, the lower the likelihood of owning two vehicles compared to own one vehicle. Households in areas with more workplaces available tend to have fewer vehicles presumably due to the lower distance journey to work travel needs.

- The more the householder lives far from the Adelaide CBD, the more is the likelihood of owning three or more vehicles.. One reason is that a large part of travels are ended in CBD as the dominant activity centre.
- Public transport coverage variable isn't proven to be significant; however this variable improved the explanatory power of the model. It may be due to high level of service (LOS) of transit coverage in most areas of metropolitan Adelaide - over 80%- thus rates of vehicle ownership are less affected by LOS. However, in order to study the impact of public transport service indicators, it is worth testing the others aspects of public transport services such as LOS-frequency and LOS-hours of operation. Also, land use mix and street layout are insignificant to explain the level of vehicle ownership as well.
- The last column of the table 3 labelled "Exp (B)" shows the odds ratios. The larger odds ratios within a tier indicate which variables have the most effect for that tier's category of the vehicle ownership level. It can also be used to interpret the model in quantative terms. When the independent variable (for example, no. of members) increases one unit, the odds of the dependent (car ownership = 3 or more) increase by a factor of 2.084.

The findings are consistent with previous empirical research, notably Holtzclaw et al.(1994) and Hess and Ong (2003) who found that average auto ownership was affected by urban spatial attributes such as density in addition to socio-economics. The results tend to lend some support to popular planning movements such as *Smart Growth* and *New Urbanism*, which suggest that auto-dependency is increased by segregated uses and low density. These findings support the contention that suburban development of metropolitan Adelaide induces higher ownership and use of private vehicles. For example, the newly designed outer suburbs: Golden Grove and Mawson Lakes have moderately higher car uses whereas the density and diversity of them are lower than the median features of metropolitan Adelaide (Soltani & Allan 2004). Hence, a part of car-dependency concern in Adelaide can be addressed through making reforms in spatial planning policies and guidelines.

In conclusion, this paper developed and implemented an empirical model that incorporates built environment features into the vehicle ownership model. The result provides evidence that urban structure attributes are important determinants of decision making on vehicle ownership. Some features of urban structure such as density and jobs-housing balance have varying degrees of influence on vehicle-ownership levels. However previous research has paid less attention to these factors as exogenous to vehicle ownership analysis. The results of this analysis support the hypothesis that while physical urban attributes are important, they are not the sole factor that impacts on a householder's decision to own a vehicle. This finding provides useful information that significantly advances knowledge on the studies of transportation – land use interaction.

5 Policy implications and further research

This study shows that urban structure is a significant contributing factor in a householders' decision to own a vehicle. It is important for planners to determine what role each factor has in a decision-making process. Therefore, the outcomes can be helpful for planners because they suggest how elements of urban structure can be also used to address essential concerns about car-dependency. While there has been little empirical research on the relationship between urban structure and vehicle ownership especially on the content of Australian cities, this study can be considered as a primary step towards the comprehensive study in this area. The findings also emphasis the importance of built form features that are qualitative yet absent from the relevant literature suggesting that urban form should be given more attention in transport policy making. This study can inform the developmental process by providing insight into the impact of land use patterns decision on making a community. The new communities build in Metropolitan Adelaide should be accessible and accommodating to multiple modes and users of transportation.

An important direction for further work is to examine the specification of these models in more detail. The effects of urban structure on vehicle ownership depend on several un-observed factors. Also the potential correlation between the urban-based regressors and un-observed heterogeneity must be controlled. This can be a subject of more detailed analysis. In addition, research may need to go much further in developing forecasts that consider the indirect casual relationship between the urban structure and vehicle-ownership.

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