The Interaction Effects in the Relationship Between Urban Form and Sustainable Transportation

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Abstract: The relationship between urban form and sustainable transportation has been extensively explored in the existing literature, and it is generally accepted that an urban form characterized by higher density, mixed land use pattern and higher accessibility could shorten travel distance and encourage people to choose alternative non-auto travel modes, which in turn reduces the fuel consumption and associated GHG emissions. However, the extensive research on urban form and sustainable transportation has only identified significant correlations between individual urban form variables, such as urban density, land use mix or road connectivity and the one or multiple sustainable transportation outcomes, such as travel mode or vehicle miles travelled (VMT), but very limited empirical studies have been identified to examine the interaction effects that may exist between the urban form attributes. This paper proposes the hypothesis that interaction effects exist between urban form attributes when examining their influences on sustainable transportation. Taking all cities in Florida, U.S. as a case, the interaction effects in the relationship between urban form and sustainable transportation are tested with empirical data. The regression results verified our hypothesis that density shows “threshold negative-to-positive” synergy with other urban form variables, indicating that certain theoretical correlations between urban form variables and sustainable transportation outcomes are conditional depending on the interactions between or among urban form attributes. The results may expand the theoretical framework on the topic of land use and transportation and has considerable policy implications for planning support systems.

1. INTRODUCTION

Topics on transportation are arguably the biggest issues in the urban form and environmental debate (Jenks, Burton, & Williams, 1996), and they have received considerable attention according to our extensive literature review. The transportation sector plays a crucial role in controlling energy consumption and GHG emissions (Bento et al., 2005; Frank, L. D. et al., 2005). From 2013 to 2017, the U.S. Energy Information Administration (EIA) reported the energy consumed by the transportation sector alone has reached 24% of the total energy consumption. The transportation sector is also reported to have contributed over 28% of the total GHG emissions in 2009.

From the perspective of travel behaviour, fewer trips, shorter travel distance and time, minimal modal interchanges, and use of public transit are
considered more sustainable (Loo & Chow, 2008). In urban studies, transportation sustainability has rich contents, generally represented by characteristics including high level of accessibility, shorter travel distance and/or duration, environmentally efficient transport modes, using renewable energy, producing less emissions, and emphasis on public transportation and social equity (Nicolas, Pochet, & Poinboeuf, 2003). It is agreed that travel is a means for overcoming spatial barriers to participate in socio-economic activities, not an end in and of itself. Therefore, travel behaviours can be affected by land use and transportation planning (Pan, Shen, & Zhang, 2009; van de Coevering & Schwanen, 2006; Newman & Kenworthy, 1999). Since then, studies have been emerging linking urban form and travel behaviours, and transportation sustainability in general, and the evidence that certain urban form attributes are positively associated with sustainable transportation is accumulating (Hamin & Gurrnan, 2009; Krizek, 2003; Zhao, 2010).

2. LITERATURE REVIEW

It is widely accepted that travel behaviours could be effectively modified through land use and transportation planning (Newman & Kenworthy, 1999). An individual would consider the cost and benefit, in terms of time, fuel, comfort and safety, when deciding which travel mode to take (Frank, L. et al., 2008; Gardner & Abraham, 2007). Evidence has been provided demonstrating the cost of travel could be changed by land use and urban design, which in turn alter the travel behaviours (Walsh et al., 2006; Zellner et al., 2008; Zhao, 2010). Arguments have been made that higher urban density is positively associated with the decline of car ownership, the increase of public transit share, both of which have resulted in the reduction of vehicle miles travelled (VMT), and the corresponding energy consumption (Jabareen, 2006; Walsh et al., 2006; Muñiz et al., 2005). A mix of different land uses brings compatible urban functions, such as home, work and play, to close proximity, which in turn shortens the distances for commuting, shopping and leisure trips (Van & Senior, 2000; Cervero, 1998).

The relationship between urban form and travel behaviour has been well identified and discussed in the existing studies. An influential study by Newman and Kenworthy (1999) was among the first to empirically examine the correlations between density and transportation energy consumption. Their results from 32 cities in Europe, North America, Australia, and Asia provide evidence that higher density is associated with less energy consumed by transportation.

Evidence supporting the association between urban form and sustainable transportation is accumulating around the world. Residents in traditional neighbourhoods, most of which are densely populated, characterized by having better accessibility to shops and services, and pedestrian friendly design is associated with more sustainable transportation (Hankey & Marshall, 2010; Kenworthy, 2006). Gordon and Richardson (1997) found that centralized urban form reduces the average distance between home and work, which leads to less energy consumed by commuting. Rajamani et al. (2003) found that development featured by mixed land use encourages walking for non-work activities. A survey was conducted by Krizek (2003), who interviewed households after they moved to neighbourhoods with different urban form attributes than their previous houses. The survey showed that the travel distance, number of trips per tour, and time spent per trip all drop when households move to a neighbourhood with higher accessibility. A case study
in China showed pedestrian and cyclist friendly neighbourhoods could discourage automobile use due to the reduced trip distance (Pan, Shen, & Zhang, 2009).

Notably, urban form attributes only play partial roles in affecting travel behaviour, and the direct influence is still debated. Studies have shown that factors such as culture, personal habit and preference, socio-economic status, climate, transportation management, transportation frequency, and general safety play significant roles in determining travel behaviours (Bamberg, Hunecke, & Blöbaum, 2007; Gardner & Abraham, 2007; Vredin Johansson, Heldt, & Johansson, 2006).

The concept of interaction effect is not new in travel behaviour studies. Research has been done to examine the interaction affects between socio-demographic characteristics and how they affect travel behaviours, such as age, income, education, life stage, gender, and social norms (Kattiyapornpong & Miller Kenneth, 2009; Kattiyapornpong, 2006; Pas, 1984; Ru et al., 2018). Some scholars have tried to further explore the interactions between the built environment and socio-demographic characteristics, such as gender (Wang, Chai, & Li, 2011), social interaction (Sidharthan et al., 2011), gasoline prices (Lee & Lee, 2013), and travel attitudes (Cao, 2015).

Studies that look at the interaction effects between urban form variables also exist but are limited to theoretical model experiments or empirical analysis in a single city. For example, Ou, Tang, and Wang (2010) discussed how residential density, distribution type, attraction ratio, and their interaction effects are performing in a computational experiment that analysed how land use influences the traffic systems. Taking the suburban development in Seoul as a case, Jun et al. (2013) empirically examined the effects of population density and its interaction effects with the size of the development on commuting modes, finding that suburbanization and density are corroborative in encouraging automobile use.

Our literature review indicates that extensive studies have been conducted discussing how urban form may affect sustainable transportation. However, most empirical studies only examine how individual urban form variables, such as population density, mix of land use and road connectivity, could influence transportation, but very limited research has looked into the interaction effects between urban form variables. This paper proposes the hypothesis that the interaction effects not only exist between socio-demographic characteristics, just as what have been found in the previous studies, but also exist between built environment attributes, or urban form variables in this study. An empirical analysis is conducted for all cities in Florida, U.S. to justify the hypothesis.

3. DATA AND METHOD

3.1 Unit of analysis

Extensive studies have been done discussing the relationship between urban form and sustainable transportation, at a different geographic scale ranging from micro level streets and neighbourhood, to macro level city and region. There is no consensus of which scale best reveals the relationship, but rather the selection of scale is determined by the research question. In this study, city is selected as the unit of analysis to empirically examine the correlations between urban form and sustainable transportation for: (1)
administrative cities have clear boundaries for measuring their size, shape, spatial patterns, and other urban form attributes; (2) performance or outcomes of sustainable transportation can be quantitatively measured within city limits, especially in Florida, where city agglomeration is relatively weak and many cities are isolated and surrounded by large rural areas; (3) the U.S. Census Bureau and other agencies have various and abundant data at city level, which facilitates our systematic empirical analysis; (4) Florida has more than 200 municipalities, which provides a sufficient sample size for regression analysis.

The data availability is the main concern when the temporal frame of this empirical analysis is determined, as extensive variables are included in the following regression analysis. In our empirical study, two major urban form variables, daytime population density and land use mix are calculated with 2012 data, which was the latest data we can get at the time this analysis was being carried out. The daytime population density considers the people who work in a city during normal business hours, so the Census population data that only counts people by where they live cannot capture the real daytime population. Therefore, we have to collect employee data from the U.S. Economic Census to locate the workplace, and use the Longitudinal Employer-Household Dynamics (LEHD) dataset to calculate the movement of employees across city boundaries.

Concerning the U.S. Economic Census, city level employee data are surveyed and published every 5 years, and at the time this study was conducted, we were able to access the 2012 data (2017 data was not accessible until early 2019). Admittedly, the 2012 data is out of date to some extent, and thus has limited power to reveal the current situations in the State of Florida. However, the 2012 data does have the power to justify the existence of the interaction effects between urban form variables, which is the main purpose of this study. Fortunately, we are now able to access the latest 2017 Economic Census data, and our study could be duplicated with additional data to (1) enhance the robustness of the regression analysis by incorporating two-year panel data; and (2) examine whether such interaction effects could be found in 2017 and consistent with 2012 models.

3.2 Description of data

Neither urban form nor sustainable transportation could be measured by a single variable, and to quantify such concepts requires extensive data from multiple sources. A list of the data we collected for the following empirical analysis is shown in Table 1, including the name of the dataset and the agency or organization that provides the data.

| Dataset Description                     | Data Source                          |
|----------------------------------------|--------------------------------------|
| American Community Survey              | U.S. Census Bureau                   |
| Economic Census                        | U.S. Census Bureau                   |
| Longitudinal Employer-Household Dynamics | U.S. Census Bureau                   |
| TIGER/Line GIS shapefile               | U.S. Census Bureau                   |
| Assessment roll GIS                    | Florida Department of Revenue         |
| FDOT Transportation Data & GIS Library | Florida Department of Transportation  |
| Florida Transit Data Exchange          | Florida Department of Transportation  |
Data processing has been done to generate the variables needed in the regression analysis based on the raw data collected. For example, daytime population, rather than the Census population, is used for calculating urban density, which incorporates the data of the American Community Survey (ACS) total population, employed population, as well as the employee data from the Economic Census. Moreover, the land area used for calculating density is aggregated from the parcel map published by The Department of Revenue tax roll GIS database.

### 3.3 Interaction effects

A well-known multiple regression model could be expressed as:

\[
y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \epsilon_i , \text{ where:}
\]

The coefficient \( \beta_1 \) refers to the effect of \( x_{i1} \) on \( y_i \);
the coefficient \( \beta_2 \) refers to the effect of \( x_{i2} \) on \( y_i \).

The interaction effects between the independent variables emerge when an independent variable’s effect is also determined by another one or more independent variables. For instance, assuming the effect of \( x_{i1} \) on \( y_i \) also depends on the value of \( x_{i2} \), the model becomes:

\[
y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_1 \beta_2 x_{i1} x_{i2} + \cdots + \beta_p x_{ip} + \epsilon_i , \text{ where:}
\]

The coefficient \( (\beta_1 + \beta_2 x_{i2}) \) becomes the effect of \( x_{i1} \) on \( y_i \);
the coefficient \( (\beta_2 + \beta_1 x_{i1}) \) becomes the effect of \( x_{i2} \) on \( y_i \).

The inclusion of the interaction term \( \beta_1 x_{i1} x_{i2} \) significantly alters the interpretations of the model and results. The original main effect coefficient \( \beta_1 \) refers to the expected change in \( y_i \) associated with a one-unit change in \( x_{i1} \), while \( x_{i2} = 0 \). However, if 0 is not in the range of meaningful values of \( x_{i2} \), the coefficient of \( x_{i1} \) may or may not be of any interest. The new coefficient \( \beta_1 \) of the interaction term tells how much effect \( x_{i2} \) has on the effect of \( x_{i1} \) on \( y_i \). Further, if \( \beta_1 \) has a positive value, an increase of \( x_{i2} \) would result in an increased effect of \( x_{i2} \) on \( y_i \) from \( x_{i1} \), while the opposite effects occur if the coefficient is negative.

Our extensive literature review has only identified limited study of interaction effects considered in the regressions. However, we argue that the potential interaction effects between or among urban form variables could not be neglected when analysing their impacts on sustainable transportation. For example, we may ask whether road connectivity influences the commuters’ modal choices to the same extent in cities with higher density as in low density cities. In this study, we assume that there are potential interaction effects between urban form variables, especially when considering different urban density. For each model, two sets of regression analyses are conducted, one with interaction terms while the other without.

### 3.4 Regression Models and Variables

Evidence from existing studies support the argument that urban forms featuring higher urban density, mixture of land use, and interconnected road networks are positively associated with sustainable transportation outcomes. As such, form contributes to the decrease of non-auto travel and the
corresponding VMT reduction through bridging the distance between origins and destinations.

Regression models are established to examine the hypothetical correlations between specific urban form variables and sustainable transportation outcomes. In each model, a sustainable transportation outcome is selected as the dependent variable, and the theoretically correlated urban form variables are included as independent variables. Admittedly, urban form only plays a partial role in affecting transport-related behaviours; other socio-economic and demographic attributes should be controlled when quantifying the influences from urban form. We include control variables, or their best available proxies based on both the extensive literature review and to the best of our knowledge. The dependent and independent variables in the regression analysis are defined as follows:

1. **Commuting mode.** Due to the data limitation at city level in Florida, we employ the commuting mode as a best proxy of travel mode, although it only records the travel activities between home and work. According to the American Association of State Highway and Transportation Officials, commuting trips constitute 28\% of total household vehicle miles travelled, and 39\% of all transit passenger miles of travel in 2013. The American Community Survey (ACS) publishes commuting mode data every year at multiple geographic scales. The data lists the percentage of the employed population who go to work by car, truck or van, public transportation, walking, cycling, or who work from home. Four dependent variables are defined referring to the theoretical correlations between urban form and travel behaviours identified in the literature, including: (1) the percent of commuting made by car, truck or van (either drive alone or car-pooled), (2) the percent of commuting made by public transit, (3) the percent of commuting made by walking, and (4) the percent of commuting made by bike.

2. **VMT per capita.** The data that records the energy consumption in the transportation sector, such as its fossil fuels, also faces limitation in Florida at city scale. In this empirical test, we employed VMT as the best proxy of the energy consumption. The U.S. Federal Highway Administration only compiles monthly VMT statistics at national and state level, but there is no ready-to-use data at city scale. Fortunately, the Florida Department of Transportation GIS database provides the Annual Average Daily Traffic (AADT), which can be used to calculate VMT in each city. VMT is calculated as “VMT = \( \sum (L_i \times AADT_i) \)”, where \( L_i \) is the length of the road segment \( i \), and \( AADT_i \) is the annual average daily traffic on the segment \( i \). To enable the VMT to be comparable among cities, the number is further calculated on per capita basis. The base population for per capita VMT calculation includes not only the permanent residents, but also people who commute to the city but live outside it, as all these people are potentially contributing to the total VMT recorded on the city roads.

3. **Density.** Population density is used as an urban form variable in the regression analysis. However, population data from the ACS only captures the number of permanent residents within the city limits. However, most of the commuting activities and non-work trips happen during the daytime; the real population density in the daytime should be considered in the analysis. As stated earlier, the daytime population is calculated as the residential population minus people who live in the city but work outside, and plus the workers who commute to the city
but live elsewhere. However, it should be noted that using daytime population density in the VMT model has some inevitable bias when considering weekend transportation activities.

(4) **Concentration.** Galster et al. (2001) defined concentration as “the degree to which development is located disproportionately in relatively few square miles of the total urban area rather than spread evenly throughout.” They measure concentration by drawing multiple one-mile square grids in a place, and then calculate “very high-density grids” (with respect to housing units or employees) as a percentage of all grids with developable land within the Urban Areas (UA). Very high-density grids are defined as “the grids that have the density two standard deviations or more above the mean of all grids in the 100 largest UAs (or in a sample of the 100 largest UAs).” Based on data availability and operational feasibility, this study makes some revisions to Galster’s approach. First, this study uses Census Block Groups as the unit of analysis, instead of artificially drawn grids, in order to keep demographic data intact. Second, this study uses floor area ratio (FAR) as a measure of density, instead of housing unit density or employee density, to avoid mass calculation of daytime population and night-time population density. Third, this study defines high density Census Block Groups as the top 25% of all block groups in Florida. Fourth, this study uses the percentage of living and usable area in high density blocks instead of the percentage of land area in high density block groups.

(5) **Land use mix.** Land use mix demonstrates the extent to which urban development blends residential, commercial, industrial, cultural, governmental, and institutional uses, as well as open space, within its land. The entropy index, which was first used in ecology and communications, is now the most widely used measurement of land use mix in urban studies. In an urban context, the entropy index can be expressed as: “Entropy Index (EI) = \( \sum A_{ij} \times (\ln(A_{ij})/\ln(N_j)) \),” where \( A_{ij} \) is the proportion of land use \( i \) in Census Block Group \( j \), and \( N_j \) is the total number of land uses considered in Census Block Group \( j \). In this study, the theoretical correlations between urban form and sustainable transportation that involve land use mix focus on how this mix brings home, work, and services together. Therefore, three land use categories are defined as residential (home), commercial/industrial (work and service), and governmental/institutional (service and work). The Florida Tax Roll GIS Database provides parcel maps for all cities in the state, and thus provides us the finest scale land use data for land use mix calculation. The entropy index is calculated for each Census Block Group and aggregated to city level using residential population as weights. The entropy index ranges from 0 to 1, where 0 indicates that there is only a single land use within the city, while 1 means a “perfect” mix. However, it should be noted that the “perfect” mix does not signify the best configuration of land use for real world cases, and it is beyond the scope of this paper to discuss the proper ratio of land use mix.

(6) **Connectivity.** In urban studies, connectivity is used to describe the state of transportation networks’ connectedness or interconnectedness. Higher connectivity is seen as a key attribute in sustainable cities in New Urbanism (Dill, 2004). In the existing urban studies, connectivity has been quantitatively measured using various indicators, including but not limited to the size or length of blocks, density of roads or intersections, and urban grid pattern, among which density of intersections is the most frequently used indicator. More road
intersections imply the street network is well connected, and also refers to more alternative routes between origins and destinations, both of which potentially shorten the trip length and encourage non-automobile travel behaviours. To be consistent with the previous studies on sustainable transportation, connectivity in the following empirical analysis is also calculated as the density of intersections within the city boundary.

(7) **Control variables.** We have added control variables in the regression analysis, including the percent of population living in their place of working, the age and gender of the employed population, car ownership, income, density of bike lanes, sidewalks and public transit stops, and total population.

## 4. RESULTS

For each model created, two regression analyses are conducted, one with interaction terms added between population density and the other urban form variables, while the other without (See Table 2 and Table 3 for the regression results). It’s noted that the control variables are added in the regression, but are not shown in the tables below, since we put our focus on effects from the urban form variables.

### Table 2. Regression results between urban form and commuting modes

| Variables                      | Percent Commuting by car | Percent Commuting by car | Percent Commuting by transit | Percent Commuting by transit | Percent Commuting by bike | Percent Commuting by bike | Percent Commuting by walk | Percent Commuting by walk |
|--------------------------------|--------------------------|--------------------------|------------------------------|------------------------------|----------------------------|----------------------------|----------------------------|----------------------------|
| ln(daytime population density) | -2.594***                | 4.382**                  | 0.603                        | -1.552                       | 0.0103                     | 0.247                     | 0.353                     | -1.540*                    |
|                                | (0.680)                  | (2.045)                  | (0.367)                      | (1.111)                      | (0.177)                    | (0.721)                    | (0.243)                    | (0.872)                    |
| Concentration                  | -1.249                   | -0.113                   | 9.086*                       | 0.358                        | 2.294                      | 0.819                      | 9.350**                   |
|                                | (1.153)                  | (9.842)                  | (0.429)                      | (4.818)                      | (0.346)                    | (2.971)                    | (0.520)                    | (4.460)                    |
| Land use mix                   | 3.875**                  | 36.99**                  | -1.641**                     | 7.900                        | -0.286                     | -3.632                     | 0.144                     | 11.55*                     |
|                                | (1.544)                  | (16.78)                  | (0.771)                      | (8.271)                      | (0.350)                    | (6.587)                    | (0.665)                    | (5.877)                    |
| ln(connectivity)               | 0.459                    | 14.42***                 | 0.178                        | -6.679***                    | -0.120                     | 0.413                      | -0.0651                   | -6.590***                  |
|                                | (0.709)                  | (3.541)                  | (0.326)                      | (2.196)                      | (0.137)                    | (1.358)                    | (0.347)                    | (2.032)                    |
| ln(density) #                  |                          |                          |                              |                              |                            |                            |                            |                            |
| Concentration                  |                          |                          |                              |                              |                            |                            |                            |                            |
| ln(density) #                  |                          |                          |                              |                              |                            |                            |                            |                            |
| Land use mix                   |                          |                          |                              |                              |                            |                            |                            |                            |
| ln(density) #                  |                          |                          |                              |                              |                            |                            |                            |                            |
| ln(connectivity)               |                          |                          |                              |                              |                            |                            |                            |                            |
| Constant                       | 145.9***                 | 75.31***                 | -5.355                       | 14.97                        | 2.460                      | 1.310                      | -4.629                    | 7.942                      |
|                                | (22.90)                  | (28.90)                  | (8.254)                      | (13.11)                      | (5.090)                    | (8.938)                    | (7.976)                    | (9.488)                    |

| Observations                  | 246                      | 246                      | 198                          | 198                          | 177                        | 177                        | 244                       | 244                       |
| R-squared                     | 0.478                    | 0.513                    | 0.497                        | 0.550                        | 0.590                      | 0.592                      | 0.289                     | 0.358                     |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
To validate the regression models, we also conducted a robustness check to make sure the core variables in the models are reasonably selected and have consistent effects on the dependent variables. We used land use area, which is another indicator of city size to replace the originally used total population, and ran all the models again to compare the results. It can be seen from Table 4 that the previous models all pass the test, and there are few significant changes in the influence of these explanatory variables, which indicate that the regressions in Table 2 and Table 3 are valid and robust.

**Table 3. Regression results between urban form and VMT per capita**

| Variables                              | ln(VMT per capita) | ln(VMT per capita) |
|----------------------------------------|--------------------|--------------------|
| ln(daytime population density)         | -0.597***          | -0.426             |
| (0.120)                                | (0.433)            |
| Concentration                          | 0.0716             | 3.128              |
| (0.176)                                | (1.912)            |
| Land use mix                           | 0.560**            | 3.380              |
| (0.231)                                | (2.674)            |
| In(connectivity)                       | 0.193**            | -0.0738            |
| (0.0874)                               | (0.704)            |
| In(density) # Concentration            | -0.369             |                    |
| (0.231)                                |                    |
| In(density) # Land use mix             | -0.332             |                    |
| (0.319)                                |                    |
| ln(density) # ln(connectivity)         | 0.0331             |                    |
| (0.0868)                               |                    |
| Constant                               | 6.098***           | 4.480              |
| (0.593)                                | (3.505)            |
| Observations                           | 242                | 242                |
| R-squared                              | 0.204              | 0.218              |

Robust standard errors in parentheses

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

**Table 4. Robustness check of the regression results**

| Variables                              | Percent Commuting by car | Percent Commuting by transit | Percent Commuting by bike | Percent Commuting by walk | ln(VMT per capita) |
|----------------------------------------|--------------------------|------------------------------|----------------------------|----------------------------|--------------------|
| ln(daytime population density)         | 4.065**                  | -1.571                       | -1.498*                    | -1.52*                    | -0.420             |
| (2.121)                                | (1.132)                  | (0.853)                      | (0.865)                    | (0.419)                    |
| Concentration                          | -10.194                  | 9.119*                       | 9.180**                    | 9.336**                    | 2.928              |
| (9.859)                                | (4.786)                  | (4.260)                      | (4.410)                    | (1.876)                    |
| Land use mix                           | 40.287**                 | 9.286                        | 10.98*                     | 11.191                     | 2.148              |
| (17.284)                               | (8.551)                  | (6.027)                      | (5.791)                    | (2.485)                    |
| ln(connectivity)                       | 15.48***                 | -6.480***                    | -6.381***                  | -6.717***                  | -0.239             |
| (3.751)                                | (2.063)                  | (2.018)                      | (2.05)                     | (0.676)                    |
| In(density) # Concentration            | 1.126                    | -1.098*                      | -1.003*                    | -1.028                     | -0.349             |
| (1.218)                                | (0.581)                  | (0.518)                      | (0.535)                    | (0.228)                    |
| ln(density) # Land use mix             | -4.584**                 | -1.225                       | -1.197*                    | -1.252*                    | -0.189             |
| (2.066)                                | (1.0350)                 | (0.682)                      | (0.699)                    | (0.301)                    |
| ln(density) # ln(connectivity)         | -1.820***                | 0.82***                      | 0.762***                   | 0.821                      | 0.0443             |
| ln(connectivity)                       | (0.46)                   | (0.249)                      | (0.235)                    | (0.247)                    | (0.084)            |
| Constant                               | 70.316***                | 13.899                       | 7.765                      | 8.266***                   | 5.613              |
| (29.483)                               | (12.527)                 | (9.258)                      | (9.457)                    | (3.33)                     |
| Observations                           | 246                      | 198                          | 244                        | 244                        | 242                |
| R-squared                              | 0.568                    | 0.572                        | 0.425                      | 0.398                      | 0.232              |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
4.1 Models without interaction effects

In all models regressed, density exhibits the most robust and significant correlations with sustainable transportation outcomes, particularly in explaining trips made by automobiles, such as commuting made by car and VMT per capita. The negative coefficients of density in our findings confirm that daytime population density is positively associated with reduction of car trips due to the shortened distance between destinations, as well as the availability of alternative transportation modals, again in conformity with previous studies. Surprisingly, density in these models without interaction terms shows no correlation with commuting activities made by public transit, bike, or walking. However, when interaction effects are considered, the expected influences from density become significant, as discussed in the next section.

Compared with the regression results of density, land use mix in the models shows much weaker correlation when significant, and the results are inconclusive. While density shows positive correlations with more environmentally sustainable transportation outcomes, such as the percent of commuting by car, the effects of land use mix on car usage show contrary results from the theoretical expectations. The results indicate a positive association between land use mix and auto commuting, but negatively correlate with commuting by public transit. In addition, the correlation between land use mix and VMT per capita also resulted in positive coefficients. Theoretically, a mix of different land uses brings home, work and play together, which in turn shortens the trip distance and promotes more environmentally efficient travel patterns. However, the regression results in Florida imply that higher land use mix is associated with the contrary results. One possible reason that may explain this outcome, especially for VMT per capita, is the induced travel, which means people are induced to travel more often when the trip distances for activities are significantly reduced.

Connectivity is only significant in the VMT model. Similar with land use mix, the resulting effect from connectivity on VMT per capita also runs counter to the theoretical underpinnings, with a positive coefficient, indicating higher connectivity correlates with more VMT. Again, induced travel could be a possible explanation: with well-connected road networks, price of travel goes down in both time and money costs, thus inducing a greater travel demand.

4.2 Models with interaction effects

The interaction terms, where significant correlations are shown in the models, always have the opposite sign as the main effect coefficient, indicating the synergy effects between density and other urban form variables. When interpreting the models with interaction effects considered, the results are more complex. For example, in the commuting by walking model, both the density*concentration and density*land use mix interaction terms have negative coefficients, implying that concentration and land use mix would have positive effects on the percent of commuters who walk to work, but only when density is at a relatively low level. Meanwhile, when density increases, the ultimate effects from concentration and land use mix become positive. In other words, the expected positive effects on encouraging walking for commuting purposes from higher concentration and land use mix could only be realized in higher density scenarios. Connectivity, on the contrary, shows
negative effects when density is low, but increasing density would make the coefficient change. The interpretation of the effect from density is more complex as three interaction terms needed to be considered. In cities with both higher concentration and balanced mix of land uses, but low connectivity, density demonstrates a negative effect on walking commuting. However, if connectivity increases, higher density is associated with more walking activities, at any level of concentration and land use mix. Essentially, the ultimate effect of density greatly depends on the level of connectivity.

Concerning the effects of urban form variables on car commuting, both land use mix and connectivity have positive coefficients when density is relatively low, but become negative when density increases. Such results illustrate that the expected effects from land use mix and connectivity on reducing auto commuting could be only realized when a certain daytime population density level threshold is reached. A lower land use mix level would make the effect from density positive, independent of the level of connectivity, but when land use mix increases, the effect of density will depend on the level of connectivity and shows a negative effect on discouraging auto commuting at a higher connectivity level. The inclusion of the interaction terms between urban form variables allows for a greater understanding of the relationship between urban form and sustainable transportation.

5. CONCLUSION AND DISCUSSIONS

Five models are established in this study to empirically test the correlations between urban form and sustainable transportation. The regression results show that the urban form variables are significantly associated with the sustainable transportation outcomes, and the results also demonstrate that interaction effects are between the independent urban form variables in explaining the dependent variable. The interaction effects between density and the other urban form variables are found to be in the form of “threshold negative-to-positive” synergy, indicating that the expected effects from higher urban density on sustainable transportation can only be obtained when other urban form variables reach certain levels simultaneously.

The findings of this paper are critical in uncovering the relationship between urban form and transportation sustainability, especially when evidence supports the existence of interaction effects between urban form variables. Some expected correlations between urban form and sustainable transportation are not supported by empirical data when interaction effects are not included, but show significant and robust association when interaction terms are added. The findings of this paper have significant implications for planners and policy makers in evidence-based planning. For example, if planners aim to promote non-automobile travel by increasing urban density in a district, their expected outcomes from increased density would not take effect unless higher concentration and land use mix are promoted at the same time. In addition, the existence of negative synergy between urban form variables warns planners to avoid modifying certain urban form attributes simultaneously, as the interaction effects would reduce the effectiveness and efficiency, or even deliver undesired outcomes.

Looking back, we believe this paper contributes to the literature on the relationship between urban form and sustainable transportation mainly in two aspects. First, this study supports the findings of previous studies that urban form variables, such as density, land use mix and connectivity have different
but significant impacts on commuting modes and travel behaviours in general. It extends the literature by proposing and testing the hypothesis that interaction effects play a role between urban form variables when considering their influences on sustainable transportation. Our empirical results imply that density shows “threshold negative-to-positive” synergy with other urban form variables, which verifies our hypothesis. Second, this study has both theoretical and practical implications. The theoretical framework of the relationship underlying urban form and sustainable transportation could be expanded, since individual urban form variable effects on sustainable transportation outcomes may depend on other urban form variables. Our findings also have potential implications in environmental behaviour science, where natural or built environment characteristics may influence people in a more synergistic way. This study may also contribute to the planning support system. By understanding the interaction effects between urban form variables, planning departments could come up with certain combinations of planning strategies to promote the positive synergy and avoid the negative synergy. For example, by promoting high density development and high connectivity road design simultaneously to encourage non-motorized travel.

There is still room for improvements in this study and future research. First, as stated above, the data accessibility limited our dataset and analysis to the year 2012 and has limited power to reflect the current situation. However, the latest data is now available and provides a chance for us to expand our research moving forward. Second, this paper only empirically tested the interaction effects between density and the other three urban form variables, while failing to include more complex interactions between or among concentration, land use mix and connectivity, and we hope to include such interaction terms in future exploration. This paper aims to propose the hypothesis that interaction effects exist between urban form variables, and by verifying the hypothesis with empirical analysis. We also call for wider attention be paid to future research on land use and sustainable transportation.

REFERENCES

Bamberg, S., Hunecke, M., & Blöbaum, A. (2007). "Social Context, Personal Norms and the Use of Public Transportation: Two Field Studies". Journal of Environmental Psychology, 27(3), 190-203. doi: https://doi.org/10.1016/j.jenvp.2007.04.001.

Bento, A. M., Cropper, M. L., Mobarak, A. M., & Vinha, K. (2005). "The Effects of Urban Spatial Structure on Travel Demand in the United States". The review of economics and statistics, 87(3), 466-478. doi: https://doi.org/10.1162/0034653054638292.

Cao, X. (2015). "Heterogeneous Effects of Neighborhood Type on Commute Mode Choice: An Exploration of Residential Dissonance in the Twin Cities". Journal of Transport Geography, 48, 188-196. doi: https://doi.org/10.1016/j.jtrangeo.2015.09.010.

Cervero, R. (1998). The Transit Metropolis: A Global Inquiry. Washington DC: Island press.

Dill, J. (2004). “Measuring Network Connectivity for Bicycling and Walking”. Proceedings of 83rd Annual Meeting of the Transportation Research Board, Washington, DC, pp. 11-15. Retrieved from http://reconnectingamerica.org/assets/Uploads/TRB2004-001550.pdf.

Frank, L., Bradley, M., Kavage, S., Chapman, J., & Lawton, T. K. (2008). "Urban Form, Travel Time, and Cost Relationships with Tour Complexity and Mode Choice". Transportation, 35(1), 37-54. doi: https://doi.org/10.1007/s11116-007-9136-6.

Frank, L. D., Schmid, T. L., Sallis, J. F., Chapman, J., & Saelens, B. E. (2005). "Linking Objectively Measured Physical Activity with Objectively Measured Urban Form: Findings from Smartraq". American journal of preventive medicine, 28(2), 117-125. doi: https://doi.org/10.1016/j.amepre.2004.11.001.

Galster, G., Hanson, R., Ratcliffe, M. R., Wolman, H., Coleman, S., & Freiha, J. (2001). "Wrestling Sprawl to the Ground: Defining and Measuring an Elusive Concept". Housing Policy Debate, 12(4), 681-717. doi: https://doi.org/10.1080/10511482.2001.9521426.
Gardner, B., & Abraham, C. (2007). "What Drives Car Use? A Grounded Theory Analysis of Commuters' Reasons for Driving". *Transportation Research Part F: Traffic Psychology and Behaviour, 10*(3), 187-200. doi: https://doi.org/10.1016/j.trf.2006.09.004.

Gordon, P., & Richardson, H. W. (1997). "Are Compact Cities a Desirable Planning Goal?". *Journal of the American Planning Association, 63*(1), 95-106. doi: https://doi.org/10.1080/01944369708975727.

Hamin, E. M., & Guran, N. (2009). "Urban Form and Climate Change: Balancing Adaptation and Mitigation in the U.S. And Australia". *Habitat International, 33*(3), 238-245. doi: https://doi.org/10.1016/j.habitatint.2008.10.005.

Hankey, S., & Marshall, J. D. (2010). "Impacts of Urban Form on Future Us Passenger-Vehicle Greenhouse Gas Emissions". *Energy Policy, 38*(9), 4880-4887. doi: https://doi.org/10.1016/j.enpol.2009.07.005.

Jabareen, Y. R. (2006). "Sustainable Urban Forms:Their Typologies, Models, and Concepts". *Journal of planning education and research, 26*(1), 38-52. doi: https://doi.org/10.1177/0739456X05285119.

Jenks, M., Burton, E., & Williams, K. (1996). "A Sustainable Future through the Compact City? Urban Intensification in the United Kingdom". *Environment by Design, 1*(1), 5-20.

Jun, M.-J., Kim, J. I., Kwon, J. H., & Jeong, J.-E. (2013). "The Effects of High-Density Suburban Development on Commuter Mode Choices in Seoul, Korea". *Cities, 31*, 230-238. doi: https://doi.org/10.1016/j.cities.2012.06.016.

Kattiyanpornpong, U. (2006). "Understanding Travel Behavior Using Demographic and Socioeconomic Variables as Travel Constraints". Retrieved from https://opus.lib.uts.edu.au/bitstream/10453/3076/1/2006005312.pdf.

Kattiyanpornpong, U., & Miller Kenneth, E. (2009). "Socio-Demographic Constraints to Travel Behavior". *International Journal of Culture, Tourism and Hospitality Research, 3*(1), 81-94. doi: https://doi.org/10.1108/17506180910940360.

Kenworthy, J. R. (2006). "The Eco-City: Ten Key Transport and Planning Dimensions for Sustainable City Development". *Environment and Urbanization, 18*(1), 67-85. doi: https://doi.org/10.1177/0956247806063947.

Krizek, K. J. (2003). "Residential Relocation and Changes in Urban Travel: Does Neighborhood-Scale Urban Form Matter?". *Journal of the American Planning Association, 69*(3), 265-281. doi: https://doi.org/10.1080/01944360308978019.

Lee, B., & Lee, Y. (2013). "Complementary Pricing and Land Use Policies: Does It Lead to Higher Transit Use?". *Journal of the American Planning Association, 79*(4), 314-328. doi: https://doi.org/10.1080/01944363.2014.915629.

Loo, B. P. Y., & Chow, A. S. Y. (2008). "Changing Urban Form in Hong Kong: What Are the Challenges on Sustainable Transportation?". *International Journal of Sustainable Transportation, 2*(3), 177-193. doi: https://doi.org/10.1080/15568310701517231.

Muñiz, I., Galindo, A., Angel, M., & López, G. (2005). "Decentralisation, Integration and Polycentricity in Barcelona".

Newman, P., & Kenworthy, J. (1999). *Sustainability and Cities: Overcoming Automobile Dependence*. Washington DC: Island Press.

Nicolas, J. P., Pochet, P., & Poinmbouef, H. (2003). "Towards Sustainable Mobility Indicators: Application to the Lyons Conurbation". *Transport Policy, 10*(3), 197-208. doi: https://doi.org/10.1016/S0967-070X(03)00021-0.

Ou, Y., Tang, S., & Wang, F. (2010, Sept 19-22). "Computational Experiments for Studying Impacts of Land Use on Traffic Systems". Proceedings of 13th International IEEE Conference on Intelligent Transportation Systems, Funchal, Portugal, pp. 1813-1818. doi: https://doi.org/10.1109/itsc.2010.5625289.

Pan, H., Shen, Q., & Zhang, M. (2009). "Influence of Urban Form on Travel Behaviour in Four Neighbourhoods of Shanghai". *Urban Studies, 46*(2), 275-294. doi: https://doi.org/10.1177/0042098008099355.

Pas, E. I. (1984). "The Effect of Selected Sociodemographic Characteristics on Daily Travel-Activity Behavior". *Environment and Planning A: Economy and Space, 16*(5), 571-581. doi: https://doi.org/10.1068/a160571.

Rajamani, J., Bhat, C. R., Handy, S., Knaap, G., & Song, Y. (2003). "Assessing Impact of Urban Form Measures on Nonwork Trip Mode Choice after Controlling for Demographic and Level-of-Service Effects". *Transportation research record, 1833*(1), 158-165. doi: https://doi.org/10.3141/1831-18.

Ru, X., Wang, S., Chen, Q., & Yan, S. (2018). "Exploring the Interaction Effects of Norms and Attitudes on Green Travel Intention: An Empirical Study in Eastern China". *Journal of Cleaner Production, 197*, 1317-1327. doi: https://doi.org/10.1016/j.jclepro.2018.06.293.

Sidharthan, R., Bhat, C. R., Pendyala, R. M., & Goulart, K. G. (2011). "Model for Children's School Travel Mode Choice:Accounting for Effects of Spatial and Social Interaction".
van de Coevering, P., & Schwanen, T. (2006). "Re-Evaluating the Impact of Urban Form on Travel Patterns in Europe and North-America". Transport Policy, 13(3), 229-239. doi: https://doi.org/10.1016/j.tranpol.2005.10.001.

Van, U.-P., & Senior, M. (2000). "The Contribution of Mixed Land Uses to Sustainable Travel in Cities". In Burton, E., Jenks, M., & Williams, K. (Eds.), Achieving Sustainable Urban Form (pp. 139-148). London: Routledge.

Vredin Johansson, M., Heldt, T., & Johansson, P. (2006). "The Effects of Attitudes and Personality Traits on Mode Choice". Transportation Research Part A: Policy and Practice, 40(6), 507-525. doi: https://doi.org/10.1016/j.tra.2005.09.001.

Walsh, E., Babakina, O., Pennock, A., Shi, H., Chi, Y., Wang, T., & Graedel, T. E. (2006). "Quantitative Guidelines for Urban Sustainability". Technology in Society, 28(1), 45-61. doi: https://doi.org/10.1016/j.techsoc.2005.10.008.

Wang, D., Chai, Y., & Li, F. (2011). "Built Environment Diversities and Activity–Travel Behaviour Variations in Beijing, China". Journal of Transport Geography, 19(6), 1173-1186. doi: https://doi.org/10.1016/j.jtrangeo.2011.03.008.

Zellner, M. L., Theis, T. L., Karunanithi, A. T., Garmestani, A. S., & Cabezas, H. (2008). "A New Framework for Urban Sustainability Assessments: Linking Complexity, Information and Policy". Computers, Environment and Urban Systems, 32(6), 474-488. doi: https://doi.org/10.1016/j.compenvurbsys.2008.08.003.

Zhao, P. (2010). "Sustainable Urban Expansion and Transportation in a Growing Megacity: Consequences of Urban Sprawl for Mobility on the Urban Fringe of Beijing". Habitat International, 34(2), 236-243. doi: https://doi.org/10.1016/j.habitatint.2009.09.008.