Journal of Cleaner Production 265 (2020) 121771

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

How do age structure and urban form influence household CO_2 emissions in road transport? Evidence from municipalities in Norway in 2009, 2011 and 2013

Yongping Liu*, Lizhen Huang, Erling Onstein

Department of Manufacturing and Civil Engineering, NTNU, Norwegian University of Science and Technology, Teknologivn 22, 2815, Gjøvik, Norway

A R T I C L E I N F O

Article history:
Received 31 July 2019
Received in revised form
21 March 2020
Accepted 16 April 2020
Available online 25 April 2020

Handling Editor: Zhen Leng

Keywords:
Household road transport
Age structure
Housing type
Building density

A B S T R A C T

This article investigates the influence of age structure on CO_2 emissions from household road transport by using an extended STIRPAT model plus data from 380 Norwegian municipalities for 2009, 2011 and 2013. After controlling for population, household income, age structures, household size, and different urban forms (urbanization, urban density, housing type, building density), the paper reveals that the age group responsible for the highest CO_2 emissions is 50–69, followed by 20–34 and 35–49. Moreover, compared with other groups, the road transport activities of age group 35–49 are highly constrained by household income. The paper also shows that there is an inverted U-shape relationship between household CO_2 road-related emissions and building densities. However, it indicates certain limitations on city planners when it comes to reducing household CO_2 road-related emissions by bringing the downtown area closer. Moreover, the paper also identifies a so-called compensatory mechanism supporting the hypothesis that building densities have positive effects. Furthermore, the coefficient of low-density housing is positive and significant, implying that the private gardens of low-density housing might not be the reason for the hypothesized compensatory mechanism. However, this remains a question worth investigating.

1. Introduction

It is accepted that household road transport activities are critical to the sustainability of European cities. In 2012, transport accounted for a growing share of total greenhouse gases emissions, while road transport accounted for more than two thirds of total transport emissions and about one fifth of the EU's total CO_2 emissions (Pablo-Romero et al., 2017). Moreover, 98% of passenger cars in 2016 used petrol and diesel (Pulselli et al., 2019), while the main types of household road vehicles are responsible for around 60.7% of total CO_2 emissions in the EU (European Parliament, 2019). Thus, a good understanding of household road transport behaviour can provide insights into the development of more sustainable cities.

On the other hand, most European cities are also experiencing both rapid population aging (Bardazzi and Pazienza, 2018) and reconcentrations of urban populations (European Commission, 2017). These two phenomena will have a significant influence on urban CO_2 emissions from road transport. In fact, a lot of research is examining the effects of age structures on the environment (Liddle, 2004, 2011; 2014; Liddle and Lung, 2010; Menz and Welsch, 2012; Zhang et al., 2018).

However, the connections between age structures and emissions produce a mixed picture with no clear conclusions (Zhang et al., 2018). Some scholars claim that the 20–34 age group is the highest energy-consuming group on the road and that the aging of the population helps to decrease road energy use (Bardazzi and Pazienza, 2018; Liddle, 2004, 2011; Liddle and Lung, 2010). However, others claim that the highest energy-consuming group on the road is that aged around 41–65 (Cao and Yang, 2017; Lee and Lee, 2014; Liu et al., 2017). Furthermore, with respect to the environmental impacts of total CO_2 emissions, the 65+ age group shows conflicting results (Menz and Welsch, 2012). Some researchers claim that population aging has a positive effect on environmental impacts (Menz and Kuhling, 2011; Menz and Welsch, 2012; Y.Y. Yang et al., 2015a; York, 2007; Zhang et al., 2017), while others claim the opposite (Hasanov and Mikayilov, 2017; Ota et al., 2018). Furthermore, it has also been suggested that there is an inverted U-shaped relationship between the 65+ age group and the

* Corresponding author.
E-mail addresses: yongping.liu@ntnu.no (Y. Liu), lizhen.huang@ntnu.no (L. Huang), erling.onstein@ntnu.no (E. Onstein).

https://doi.org/10.1016/j.jclepro.2020.121771

environmental impacts (Okada, 2012; Zhang and Tan, 2016).[1]

These conflicting results (see Table 1) render interpreting the effects of age groups on the environment inconclusive (Zhang et al., 2018), creating the need for more studies on the potentially detrimental effects of age structures on the environment. The disagreements in the existing literature may reflect different data sets and different methodologies. The failure to identify different road transport behaviour patterns among age groups could be one reason, because most researchers implicitly assume that all age groups have the same road energy consumption mode given the same income level. In fact, this assumption is questionable because different age groups have different activities. For example, the <15 age group are students with fixed daily transport demands which are seldom limited by the household incomes, while the 35–49 age group are usually regarded as the household heads of large households. Therefore, it is sensible to assume that the transport activity of this group may be highly constrained by household incomes, especially in respect to long-distance leisure travel. As a result, further studies of age structures, with careful consideration being given to the income constraints on different age groups, are needed in order to investigate the effects of age structures on the environment. For example, Zhang et al. (2018) suggest that age structures have indirect effects on the environment through income levels. Therefore, by integrating the indirect effects of the age structure as well, this paper examines the effects of age structure on the household road environment using an extended STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model covering data from 380 Norwegian municipalities in 2009, 2011 and 2013. Based on a cross-sectional analysis of Norway in 2013, the findings demonstrate that the group aged 50–69 is responsible for most CO_2 road-related emissions, followed by age group 20–34 and age group 35–49. Moreover, age group 35–49 needs more attention because this group's road transport activities are highly influenced by their household incomes.

The paper is structured as follows. First, the relevant literature is reviewed. Second, the model, data and empirical strategy are presented. Third, the main estimated results are discussed. Finally, conclusions are offered.

2. Literature review

In the literature, the most popular method of analyzing the effects of age structures on the environment is Multivariate Linear Regression, initially based on the identity (I = PAT).[2] It was suggested by Ehrlich and Holdren (1971), who assume that environmental impacts, energy use or CO_2 emissions (I) are a multiplicative product of population (P), affluence/income per capita (A) and technology (T).

$$I = PAT \tag{2.1}$$

Based on this identity, an empirical analysis model (STIRPAT) has been developed by Dietz and Rosa (1997), which has the following formula:

$$I = aP^bA^cT^de \tag{2.2}$$

where, a, b, c and d are the coefficients to be estimated, and e is a stochastic error item.

Thus, the Multivariate Linear Regression on STIRPAT is as follows:

$$\ln(I) = \ln a + b\ln(P) + c\ln(A) + d\ln(T) + \ln e \tag{2.3}$$

The model can be transformed as follows:

$$\ln(I) - \ln(A) = \ln(I/A) = \ln a + b\ln(P) + (c-1)\ln(A) + d\ln(T) + \ln e \tag{2.4}$$

Thus, the energy intensity (I/A) can easily be deduced from the estimated STIRPAT model.

The STIRPAT model is widely used to analyze the effects of age structures on the environment or CO_2 emissions from energy use (Liddle, 2004, 2011; Liddle and Lung, 2010; Menz and Kuhling, 2011; Menz and Welsch, 2012; Ota et al., 2018; Pablo-Romero et al., 2017; Poumanyvong et al., 2012; Zhang et al., 2018). However, as mentioned above, the results on the effects of different age groups on the environment conflict and are inconclusive (Zhang et al., 2018). For example, Ota et al. (2018) found that the proportion of elderly in a population is significantly negative in terms of urban electricity consumption and insignificant in urban gas consumption, which conflicts with the results in Hasanov and Mikayilov (2017) and Liddle (2011) claiming that the elderly show positive elasticity in respect of residential electricity consumption. These mixed results may be due to differences in data and estimated models. Moreover, there are two possible explanations for these inconclusive results. First, it is evident that the indirect effects of age structures on the environment have received less attention from most researchers. One exception is Zhang et al. (2018), who found that the impact of age structures on the environment depends partly on the specific level of income per capita, which strongly implies that the interactivity between age structure and income should be taken into account in the estimated model. Thus, a failure to see the indirect effect of age structures on the environment by income might indicate that income has the same constraint on energy consumption behavior on the road for each of the age groups. This assumption is questionable; according to the life-cycle hypothesis, wealth grows with age during one's working life, which suggests that the 50–67 working-age group are wealthier than the 35–49 working-age group. Moreover, according to the implicit housing hierarchy hypothesis (Morrow-Jones and Wenning, 2005), it is reasonable to expect the 50–67 age group to have completed their last climb up the housing ladder and thus be in a higher position in the housing hierarchy than the 35–49 age group. Therefore, it is also reasonable to believe that the 35–49 age group will have stricter budget constraints than the 50–67 age group.

Second, few researchers have examined the impact of the urbanized area level of spatial form on the environment, due to the lack of appropriate measurements (Lee and Lee, 2014). In fact, it has been empirically verified that age structure plays a critical role in decisions regarding housing locations (Lee et al., 2016). Moreover, according to urban theory, the density of residential housing has a negative relationship with distance from the city centre (Gaigné et al., 2012), which implies that housing location is an important variable that needs to be considered in our estimated model in terms of driving distances. Hence, the failure to see the effects of housing type – one facet of urban form – are another possible explanation for the different results. Therefore, by introducing the more complete variables of urban form (urbanization, urban population density, urban building density, housing type), rate of car-ownership by low-density housing, household size, household income, age structures and the indirect effect of age structure by household income, the assessments in this paper may provide a greater understanding of the factors that influence household CO_2 emissions in road transport.

[1] The different results can be seen in Table 1.

[2] I = PAT is the mathematical notation of a formula put forward to describe the impact of human activity on the environment.

Table 1
Some conflicting empirical results of age structure on carbon emissions and energy consumption.

Dependent Variable	Date and Research Method	Age Compositions	Source	Notes on Population Ageing Effects
Log (per capita CO_2 emissions)	Panel date and first difference GMM estimators	The share of the working-age population (15–64) (The direct effect is positive and significant. The indirect effect depends on level of GDP per capita)	Zhang et al. (2018)	positive
Individual carbon emissions on weekdays	Survey date and OLS estimators	Share of Age 18–29, +3.019, 5% significant, Share of Age 30–39, +3.199, 5% significant, Share of Age 40–49, +3.259, 5% significant, Share of Age 50–59, +3.060, 5% significant,	Yang et al. (2018)	negative
Carpooling frequency index	Survey date	Sample Age distributions: 18–24 (4.8%), 25–34 (21.8%), 35–49 (37.4%), and age 50 + (36%). the correlations between age and carpooling frequency index are negative	Gheorghiu and Delhomme (2018)	unclear
Log of per capita residential electricity consumption and log of per capita residential town gas consumption	Panel date and FE, FD and PW estimators	Share of people aged 65 or above (−1.052, and significant at 1% to the residential electricity consumption, but not clear effects on city gas consumption per capita)	Ota et al. (2018)	negative
Log of the household's deflated fuel expenditure per adult	Survey date and OLS	The dummy variables for ages between 18 and 75 in 11 classes, which suggests a life-cycle pattern in fuel expenditure.	Bardazzi and Pazienza (2018)	negative
Log (total CO_2 emissions)	Panel date and FE estimators	Log of the percentage of population aged 65 and above (positive and significant)	Zhang et al. (2017)	positive
Log (CO_2 emissions)	Panel date and N−W estimators	Log of the ratio of people over 65 years old (+0.207, significant at 5% in eastern region) (-0.03, significant at 10% in central region) (-0.019, significant at 10% in western region)	Wang et al. (2017)	unclear
CO_2 emission from trips	Cross section date and SEM estimators	Share of age 16–24,Share of age 25–34 Share of age 35–44,Share of age over45 All is positive and significant	Cao and Yang (2017)	unclear
Log of residential electricity consumption	Panel date and LS estimators	Log of the number of people age 15-64 (+8.32, significant at 1%) Log of the number of people over 65 years old (+2.33, significant at 1%)	Hasanov and Mikayilov (2017)	negative
Log (CO_2 emissions)	Panel date and FD estimators	Log of share of the working-age population (15–64) (+0.45, significant at 5%)	Zhou and Liu (2016)	negative
Log (CO_2 emissions)	Panel date and GMM	Log share of age population65 and over (+42, significant at 1%) Square of log share of age population 65 and over (-17, significant at 1%)	Zhang and Tan (2016)	negative
Log (energy use per capita)	Panel date and ARDL estimators	Log share of age population (35–49) (+0.34, and significant at 1%) Log share of age population 50-64 (+0.751, and significant at 1%) Log share of age population (65–79) (+0.344, and significant at 1%)	Hasanov et al. (2016)	negative
Log (per capita CO_2 emissions)	Time series date and PLS estimators	Log share of young population (0–14) (-0.000) Log share of working population (15–64) (+0.059) Log share of ageing population (over65) (+0.065)	Yang et al. (2015a, b)	positive
Log (total CO_2 emissions)	Cross section date and OLS	Share of population 15-29 (-0.011, significant at 5%) Share of population 30-64 (-0.010, not significant)	Roberts (2014)	positive
Log (total CO_2 emissions)	Panel date and 2SLS estimators	Share of population 20-34 (-0.395, not significant) Share of population 35-49 (+5.92, significant at 5%) Share of population 50-69 (-3.846, not significant) Share of population over 70 (+5.06, not significant)	Lugauer et al. (2014)	negative
Log (total CO_2 emissions)	Panel date and FE estimators	Log of the number of people aged 15-64 (+0.069, significant at 10% in developed countries) Log of the number of people aged 15-64 (+0.038, significant at 1% in developed countries)	Leon et al. (2014)	negative
CO_2 emissions per capita from transport	Panel date and cross-section RE estimators	The share of population over 64 (+64.10, significant at 10%) Square of share of population over 64, (-2.47, significant at 5%)	Okada (2012)	negative
Log (CO_2 emissions)	Panel date and PCSE estimators	The share of population 30–44 (−1.17, significant at 5%) Share of population 45–59 (−1.77, significant at 1%)	Menz and Welsch (2012)	positive
Log (SO_2 emissions)	Panel date and PCSE estimators	Log (share of population 0–14), not significant Log (share of population over 65), not significant	Menz and Kuhling (2011)	unclear

(*continued on next page*)

Table 1 (*continued*)

Dependent Variable	Date and Research Method	Age Compositions	Source	Notes on Population Ageing Effects
Log (CO_2 emissions)	Panel date and FE estimators	Log (share of population 15–64), not significant Log (share of population over 65), not significant	Martinez-Zarzoso and Maruotti (2011)	unclear
Log (CO_2 from transport)	Panel date and FMOS estimators	Log (share of population 20–34), +0.818, significant Log (share of population 35–49), −0.217, significant Log (share of population 50–69), −0.771, significant Log (share of population over 70), −0.363, significant	Liddle (2011)	Negative
Log (residential electricity)		Log (share of population 20–34), +0.219, significant Log (share of population 35–49), −0.418, significant Log (share of population 50–69), −0.404, significant Log (share of population 70+), +0.552, significant		positive
Log (CO_2)	Panel date and FE estimators	Log (share of population 20–34), +0.2, significant Log (share of population 35–64), −0.36, significant	Liddle and Lung (2010)	Positive
Log (CO_2 from transport)		Log (share of population 20–34), +0.3, significant Log (share of population 35–64), −0.48, significant		negative
Log (residential electricity consumption)		Log (share of population 35–49), −0.303, significant Log (share of population 50–64), −0.285, significant Log (share of population 65–79), 0.174, significant		positive
Log (energy consumption)	Panel date and P−W estimators	Log (share of population over 65), +0.965, significant	York (2007)	Positive
Log (CO_2)	Panel date and PLS estimators	Log (share of population 15–64), −1.65 within high income group, significant	Fan et al. (2006)	Positive
Road energy use per capita	Panel date and FE estimators	Share of population 20–39, positive and significant	Liddle (2004)	negative

3. Model and data

3.1. Variables and model

The analysis begins with a simple identity with acronyms that are described in the following Table 2.

$$I = \frac{I}{GDP} \times \frac{GDP}{HH} \times \frac{HH}{P} \times \frac{P}{UP} \times \frac{UP}{UA} \times \frac{UA}{TBN} \times \frac{TBN}{PGH} \times \frac{PGH}{PC} \times PC$$

Thus, the identity can be rewritten further as:

$$I = \frac{I}{A} \times \frac{Gdp}{HH} \times \frac{HH}{P} \times \frac{P}{UP} \times \frac{UP}{UA} \times \frac{UA}{TBN} \times \frac{TBN}{PGH} \times \frac{PGH}{PC} \times \frac{PC}{P}$$

Therefore, we arrive at the following identity:

$$I = \frac{I}{A} \times \frac{GDP}{HH} \times HS^{-1} \times UR^{-1} \times UD \times BD^{-1} \times LR^{-1} \times LHCR^{-1} \times COP$$

The identity can be transformed with log form as follows:

$$\ln I = \ln \frac{I}{A} + \ln \frac{GDP}{HH} - \ln HS - \ln UR + \ln UD - \ln BD - \ln LR - \ln LHCR + \ln COP \tag{3}$$

There are three advantages to using this identity. First, it is easy to integrate most of the variables of urban form into the estimation model, such as household size (HS), urban density (UD), urbanization (UR), building density (BD) and the rate of low-density housing (LR) that have been identified as variables in use of transport energy (Liddle, 2004; Poumanyvong et al., 2012; Yang, W. et al., 2015b).

Table 2
The description of acronyms.

acronym	Description	Notation or unit
I	Energy use or CO_2 emissions	tons
GDP	Gross domestic product	GDP = A×P
A	Income per capita	kroner
P	Population	Total population
HH	Household	The number of family
UP	Urban population	People living in urban area
UA	Urban area	Urban area of settlements
TBN	Total building number	units
PGH	Private garden house	the number of houses with a private garden
PC	Private car	the number of private cars
HS	Household size	HS=P/HH
UR	urbanization	UR=UP/P
UD	Urban density	UD=UP/UA
BD	Building density	BD = TBN/UA
LR	the share of low-density housing	LR = PGH/TBN
LHCR	The average number of private cars owned by low-density house	LHCR = PC/PGH
COP	The average number of private cars owned by people	COP = PC/P
Y	The household income	Y = GDP/HH

Moreover, using this identity preserves a degree of freedom because of the prefect collinearity between urbanization (UR), urban density (UD), building density (BD), the share of low-density houses (LR), average vehicles owned by low-density houses (LHCR) and average private cars owned by people (COP). Therefore, in the next estimation equation, the variable of COP is not included. Thirdly, it is more convenient to quote the energy intensity (I/A) indirectly from the literature on STIRPAT models (see the equation (2.4)).

Regarding to the STIRPAT model, there are four components (see the equation (2.3)), namely, income per capita (A), population (P), technology (T) and the stochastic error item. Currently, the literature on the STIRPAT models have identified many determinant variables that serve as proxies for technology (T), such as, age composition (AC), urbanization level (UR), urban density (UD), household size (HS) and share of service income in GDP (SV) (for example, Yang, W. et al. (2015b), Poumanyvong et al. (2012), Liddle (2014), and Liu et al. (2017)). However, it can be seen there are no agreed answers regarding how many explanatory variables should be included in the estimated STIRPAT equation (Vélez-Henao et al., 2019). Due to this, the determinant variables found in the literature will be put into STIRPAT frame as much as possible within a combination of Norwegian context. Thus, the special estimated model in the literature on the STIRPAT frame between I and A can be stated as follows:

$$\ln I_i = \beta_0 + \beta_1 \ln A_i + \beta_2 \ln P_i + \beta_3 \ln UR_i + \beta_4 \ln HS_i + \beta_5 \ln UD_i + \beta_6 \ln AC_i + \beta_7 \ln SV_i + \varepsilon_i \tag{4}$$

Here, β_i is the parameter and ε_i is the error term. Like equation (2.4), this estimated equation can be transformed indirectly as follows:

$$\ln I_i - \ln A_i = \beta_0 + (\beta_1 - 1)\ln A_i + \beta_2 \ln P_i + \beta_3 \ln UR_i + \beta_4 \ln HS_i + \beta_5 \ln UD_i + \beta_6 \ln AC_i + \beta_7 \ln SV_i + \varepsilon_i \tag{4.1}$$

The right side of the equation is the log of energy intensity or energy per income. Integrating the estimated Eq. (4.1) into identity (3), the identity (3) is transformed as follows:

$$\ln I_i = \alpha_0 + \alpha_1 \ln Y_i + \alpha_2 \ln P_i + \alpha_3 \ln UR_i + \alpha_4 \ln HS_i + \alpha_5 \ln UD_i + \alpha_6 \ln BD_i + \alpha_7 \ln AC_i + \alpha_8 \ln LR_i + \alpha_9 \ln LHCR_i + \alpha_{10} \ln SV_i + \varepsilon_i \tag{5}$$

Here, income per capita (A) is substituted by median household income after tax (Y).[3] This agrees with Liddle (2004), who posits that the household is an important level of analysis for road transport, especially for passenger cars, because it is more relative to household unit than to per capita income. In addition, according to the life-cycle hypothesis (Modigliani, 1966), wealth grows with age during working periods. Therefore, it is reasonable to assume that the effects of the age composition may partly depend on income levels. After all, CO_2 emissions on the road stem from one kind of energy consumption behaviour that is constrained by income. Hence, the interactive terms between income and age structures are included in the equation. Moreover, according to urban theory, the density of residential housing has a negative relationship with distance from the city centre (Gaigné et al., 2012). Therefore, it is also reasonable to assume that people living in different types of dwelling may have different transport behaviour. Hence, the interactive terms between low-density housing and age composition are included in the assessment. Moreover, because of the so-called compensatory mechanism hypothesis (Holden and Norland, 2005) and economic scale in cities, the square of building density is also included in the model. Therefore, the estimation model is as follows:

$$\ln I_i = \alpha_0 + \alpha_1 \ln Y_i + \alpha_2 \ln P_i + \alpha_3 \ln UR_i + \alpha_4 \ln HS_i + \alpha_5 \ln UD_i + \alpha_6 \ln BD_i + \alpha_7 (\ln BD_i)\hat{}2 + \alpha_8 \ln AC_i + \alpha_9 \ln LR_i + \alpha_{10} \ln LHCR_i + \alpha_{11} \ln SV_i + \alpha_{12}(\ln LR_i \times \ln AC_i) + \alpha_{13}(\ln Y \times \ln AC_i) + \varepsilon_i \tag{6}$$

According to equation (6), the estimated parameters ($\alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_{10}, \alpha_{11}$) are the elasticity of population (P), urbanization (UR), household size (HS), average vehicles owned by low-density houses (LHCR) and share of service income (SV) respectively.[4] The income elasticity is $\alpha_1 + \alpha_{13} \times \ln(AC_i)$, which may partly depend on the value of the special age structure$\ln(AC_i)$. The building density elasticity is $\alpha_6 + 2 \times \alpha_7 \times \ln(BD_i)$, which may partly depend on the average value of building density$\ln(BD_i)$. The elasticity of the age structure is $\alpha_8 + \alpha_{12} \times \ln(LR_i) + \alpha_{13} \times \ln(Y_i)$, which may partly depend on the average value of $\ln(LR_i)$and $\ln(Y_i)$.

3.2. Date sources

The data for municipalities come from Statistics Norway (SSB). Our definition of municipalities follows the Norwegian nomenclature of 2017 (Statistics Norway, 2017). These data include light car CO_2 emissions from road transport, age composition, urban population, urban area, median household income after tax, household size, turnover per capita in the service sector, and the number of buildings and residential buildings with a private garden (see Table 3). Total population is calculated by age group, there being six groups, based on facts specific to Norway and the existing literature (<15, 16–19, 20–34, 35–49, 50–69, >70). In Norway, under-16s are not allowed to drive. People between 16 and 19 are usually students at high school, while the normal retirement age is 67. Furthermore, there are no agreed classifications of age structures in the literature. For example, Liddle and Lung (2010) divided the age structure into five groups (<20, 20–34, 35–49, 50–69, and 70+), which they argued approximate to most life-cycle periods. Menz and Welsch (2012) divided the age structure into six groups (<15, 15–29, 30–44, 45–49, 60–74, and 75+), as did Lee and Lee (2014), though differently (<21, 21–30, 31–40, 41–50, 51–65, 65+). The classifications of Liddle (2011) are followed in this study, combined with specific Norwegian features, which resulted in our division into six groups. The study period (2009, 2011, 2013) was limited by the availability of data for CO_2 emissions from light vehicles in road transport, which is restricted to 2009, 2011 and 2013 (see Table 3). Moreover, life expectancy in Norway was 83.2 for women and 78.6 for men in 2010, and 83.6 for women and 79.4 for men in 2013 (Statistics Norway, 2018). Therefore, it can be expected that the change in the age structure will be very small over brief periods, as can be proved by the value of the age structures in Table A1 and Table A2. However, the variations are larger among the municipalities. For example, the minimum value for the 20–34 age group is −2.201 and the maximum value is −1.265, which implies a minimum value for this group of 11% (=e^ (−2.201)) and a maximum value of 28% (=e^ (−1.265)) (see Table A2). Therefore, the data for 380 municipalities and a balanced panel for a period of three years (2009, 2011, 2013) provide an opportunity to explore the relationship

[3] It can readily be seen that as $GDP/population = GDP/household \times household/population$, we arrive at $\ln(GDP/population) = \ln A = \ln(GDP/household) + \ln(household/population) = \ln(Y) - \ln(HS)$.

[4] is the estimated parameter of elasticity. For example, $\alpha_2 = \partial[\ln(I)]/\partial[\ln(P)]$,which is the population elasticity of energy use on road. This suggests that one percent of change in P will lead to α_i percent of change in energy use on the road.

Table 3
Data sources.

Data	Measure	Source
light vehicle CO_2 emissions from road transport	light vehicles, including private car, moped and motorcycle	SSB, http://www.ssb.no/natur-og-miljo/artikler-og-publikasjoner/utslipp-til-luft-av-klimagasser-fordelt-pa-kommune2009,2011,2013
age compositions	the number of population aged 0 to 105;	SSB, 07459: Population by sex and age groups (M) 1986–2018
total population	the total population is the sum of all ages	
urban area	area of urban settlements	SSB, 04861: Area and population of urban settlements (M) 2000–2017
urban population	the number of residents in urban area	SSB, 04861: Area and population of urban settlements(M) 2000–2017
median household income after tax	median income after tax by household	SSB, 06944: Income after taxes, by type of household, number of households and median(M) 2005–2016
average household size	the total population/the number of household	SSB, 06944: Income after taxes, by type of household, number of households and median
the number of private transport vehicles	the sum of the passenger car plus motors	SSB, 07849: Registered vehicles, by type of transport and type of fuel(M) 2008–2017
the number of different dwellings	Units	SSB, 06265: dwellings, by type of building (M) 2006–2018
service turnover per capita	Kroner	SSB, 04776: Turnover per capita retail sales (NOK) (M) 2008–2017

Table 4
Definitions of the variables used in the estimation model.

Variables	Definitions	Units/notation
Light car CO_2 from road transport	CO_2 emissions source: light car and motors	1000 tons
co1	Ln (Light car CO_2 from road transport)	
Y	median income after tax by household	Kroner
income	Ln(Y)	
AC0_15	The share of age under15	Population under 15/total population (percent)
AC1619	The share of age between 16 and 19	Population between 16 and 19/total population (percent)
AC2034	The share of age between 20 and 34	Population between 20 and 34/total population (percent)
AC3549	The share of age between 35 and 49	Population between 35 and 49/total population (percent)
AC5069	The share of age between 50 and 69	Population between 50 and 69/total population (percent)
AC_70	The share of age between 70+	Population above 70/total population (percent)
ac0_15	Ln(AC0_15)	
ac1619	Ln(AC1619)	
ac2034	Ln(AC2034)	
ac3549	Ln(AC3549)	
ac5069	Ln(AC5069)	
po	Ln (total population)	
hs	Ln (household size)	
ur	Ln (urbanization)	Urbanization (UR) = urban population/total population (percent)
ud	Ln (urban density)	Urban density(UD) = urban population/urban area (person/km2)
bd	Ln (building density)	Building density (BD) = total building units/urban area (unit/km2)
lr	Ln (low density house rate)	Low density house rate (LR) = low density house/total building units (percent) and low density houses include: detached house, house with 2 dwellings, row house
lhcr	Ln (LHCR)	Per vehicle owned by low density houses (LHCR)=(the sum of passenger car + motors)/(the sum of low density house)
sv	Ln(SV)	The share of service income in GDP (SV)
income3549	income×ac3549	Interactive term
lr0_15	lr×ac0_15	Interactive term
lr2034	lr×ac2034	Interactive term
lr5069	lr×ac5069	Interactive term

between age structure and CO_2 emissions from household road transport. Table 4 lists the variables used, their definitions and model units. In addition, Stata 15, a software for statistical and data science from StataCorp LLC, is used to run and test the estimated parameters for all the models in this study.

3.3. Empirical strategy

Table 5 gives the estimated results of Eq. (6) by OLS (ordinary least squares) for 2013, FE with and without time effects being controlled for (fixed effects estimator), FD (first differencing estimator), RE (random effects estimator), PCSE (panel corrected standard error estimator) and pooled OLS estimator. Column 7 in Table 5 is the PCSE estimator, which only assumes the existence of groupwise heteroskedasticity. The PCSE estimator in Column 8 of Table 5 is assumed with the existence of both groupwise heteroscedasticity and contemporaneous correlation. The OLS for 2013 (Column 1 in Table 5) is against the functional form misspecification at a ten percent threshold (the p-value is 0.104 for

Table 5
Results of the estimated model.

	(1)	(2)	(3)	(5)	(6)	(7)	(8)	(9)
	ols2013	fe	fe1	Fd	re	xtpcse	xtpcse1	pooled_ols
Po	0.949*****	0.355*****	0.408*****	0.284*****	0.969*****	0.940*****	0.940*****	0.940*****
	(0.044)	(0.073)	(0.063)	(0.076)	(0.023)	(0.028)	(0.004)	(0.028)
income	11.214****	−0.690***	−0.557**	−0.344	−0.983*****	9.105*****	9.105*****	9.105*****
	(3.649)	(0.250)	(0.238)	(0.246)	(0.266)	(1.795)	(2.170)	(1.805)
hs	1.833*	0.007	−0.047	−0.048	−0.074	1.296**	1.296**	1.296**
	(0.955)	(0.062)	(0.052)	(0.047)	(0.065)	(0.511)	(0.530)	(0.539)
ur	2.849*****	0.215***	0.227****	0.142*	0.574*****	2.698*****	2.698*****	2.698*****
	(0.498)	(0.079)	(0.077)	(0.072)	(0.079)	(0.274)	(0.126)	(0.277)
ud	−2.976*****	−0.226****	−0.243****	−0.153**	−0.623*****	−2.903*****	−2.903*****	−2.903*****
	(0.444)	(0.079)	(0.078)	(0.071)	(0.077)	(0.254)	(0.106)	(0.257)
ac0_15	1.785****	0.044	0.031	0.036	−0.012	1.408*****	1.408*****	1.408*****
	(0.596)	(0.070)	(0.070)	(0.061)	(0.074)	(0.362)	(0.146)	(0.356)
ac1619	−0.534***	0.012	0.007	0.009	−0.011	−0.126	−0.126	−0.126
	(0.205)	(0.019)	(0.019)	(0.017)	(0.020)	(0.136)	(0.215)	(0.140)
ac2034	2.383*****	0.026	0.027	0.002	−0.007	1.935*****	1.935*****	1.935*****
	(0.514)	(0.049)	(0.049)	(0.043)	(0.051)	(0.279)	(0.368)	(0.277)
ac3549	−95.664****	5.135***	4.664**	2.977	8.335*****	−76.469*****	−76.469*****	−76.469*****
	(31.022)	(1.917)	(1.898)	(2.058)	(2.023)	(15.246)	(19.333)	(15.326)
ac5069	3.883*****	0.281*****	0.291*****	0.222****	0.335*****	3.273*****	3.273*****	3.273*****
	(0.910)	(0.082)	(0.082)	(0.078)	(0.088)	(0.500)	(0.424)	(0.491)
income3549	7.379****	−0.390***	−0.354**	−0.225	−0.645*****	5.950*****	5.950*****	5.950*****
	(2.387)	(0.148)	(0.147)	(0.159)	(0.156)	(1.177)	(1.492)	(1.183)
bd	8.385*****	−0.023	−0.014	−0.145	0.512*****	6.240*****	6.240*****	6.240*****
	(1.508)	(0.137)	(0.133)	(0.141)	(0.141)	(0.955)	(0.734)	(0.967)
bd2	−0.383*****	0.017**	0.017**	0.020**	0.006	−0.248*****	−0.248*****	−0.248*****
	(0.105)	(0.008)	(0.008)	(0.009)	(0.008)	(0.067)	(0.049)	(0.068)
lr	70.152*****	5.494****	5.686****	4.658****	8.844*****	48.510*****	48.510*****	48.510*****
	(17.131)	(1.823)	(1.820)	(1.556)	(1.927)	(8.591)	(10.857)	(8.682)
lr0_15	10.559****	1.546****	1.594****	1.201***	2.447*****	6.982*****	6.982*****	6.982*****
	(3.379)	(0.527)	(0.526)	(0.438)	(0.554)	(1.729)	(1.634)	(1.754)
lr2034	12.277*****	0.425	0.503*	0.414	1.149*****	8.448*****	8.448*****	8.448*****
	(3.118)	(0.305)	(0.301)	(0.287)	(0.311)	(1.535)	(1.943)	(1.556)
lr5069	21.446*****	1.380**	1.358**	1.283**	1.527***	14.911*****	14.911*****	14.911*****
	(5.374)	(0.566)	(0.563)	(0.528)	(0.581)	(2.711)	(3.382)	(2.733)
lhcr	1.588*****	0.042	0.060	0.034	0.245*****	1.579*****	1.579*****	1.579*****
	(0.249)	(0.051)	(0.049)	(0.044)	(0.052)	(0.134)	(0.039)	(0.135)
sv	0.121**	−0.000	−0.000	0.006	0.008	0.111*****	0.111*****	0.111*****
	(0.054)	(0.013)	(0.013)	(0.011)	(0.014)	(0.032)	(0.007)	(0.032)
cons	−159.019*****	9.870****	7.765***		7.975**	−123.341*****	−123.341*****	−123.341*****
	(47.545)	(3.133)	(2.864)		(3.383)	(22.968)	(29.246)	(23.061)
time effects		controlled			controlled	controlled	controlled	controlled
N	380	1139	1139	760	1139	1139	1139	1139
R^2	0.899	0.221	0.218	0.062		0.889	0.889	0.889
adj. R^2	0.894			0.038				0.887

Standard errors in parentheses.
*p < 0.1, ** p < 0.05, *** p < 0.01, **** p < 0.005, ***** p < 0.001.

Ramsey's test).[5] The results of FE, FD and RE show large differences. The small variation in age structure in 2009, 2011 and 2013 may be one reason (see Table A1and A2). The Hausman test (the p-value is 0.0000) demonstrates that the FE estimators are preferred. However, detection of the presence of heteroscedasticity is visible (the p value of a modified Wald test for group-wise heteroscedasticity is 0.0000, which shows a strong rejection of no heteroscedasticity). The test for autocorrelation within the panel data is used from FD estimators, and the result gives a p value of 0.0000, which suggests a strong rejection of no first-order autocorrelation in the panel data, given the assumption that the first-order autocorrelation coefficient is the same across sectors. Therefore, the PCSE models are applied to address these two issues.

It can be seen in Table 5 that the results from OLS for 2013, pooled OLS and OLS with a panel-corrected standard error estimator are not sensitive to the choice of the estimating method and that all variables have both the same sign and the same statistical significance. Since the results show no significant difference among the three models, the discussion focuses on a series of alternative models for 2013, which contain all the important variables and the most recent data.

Table 6 is built on the basis of the Column 1 model in Table 5. It shows how the interactive variables of the estimated model are determined and why the model ols2013 in Column 1 of Table 5 is determined. It can be seen that all the important variables (Column 1 to Column 7 in Table 6) have similar sign and statistical significance (for example, po, hs, ur, ud, ac3549, ac5069, income3549, bd, bd^2, lr, lr0_15, lr2034, lr5069, lhcr, and sv). In Columns 6 and 7 of Table 6, it can be seen that income is not statistically significant when the model begins to include the interactive items between income and age groups 0–15 and 16–19, which show no statistical significance. In Column 5 of Table 6, the income becomes significant when the interactive items are removed. Based on a comparison of the results in Columns 5, 6 and 7, the interactive items between income and age groups 0–15 and 16–19 are not considered in the model. At the same time, it can be seen that the 70+ age group and the interactive items between lr and ages 35–49 and 70+ are not significant across all models from Column 3 to Column 7 in Table 6. It is also noted that the other important variables remain unchanged in both sign and significance, while these interactive items are removed from the model (see Columns 1 and 2 in Table 6).

Therefore, based on these comparisons among columns (3–7 in Table 6), age group 70+ and the interactive items between lr and age groups 35–49 and 70+ are removed from the model. Furthermore, it is noted that the 20–34 age group is not significant with a combination of interactive items between income and age group 20–34 in the model, while all the important variables in Table 6 stay the same size with the same statistical significance (see Column 2 to Column 7 of Table 6). When the interactive item is removed, age group 20–34 becomes significant (see Column 1 of Table 6). Since the impact of the age structure is the focus of our paper, the interactive items between income and age group 20–34 are removed from the model. Thus, the models in Table 7 do not include the interactive items between income and age groups 0–15, 16–19, and 20–34, age group 70+ or the interactive items between lr and age groups 35–49 and 70+.

4. Empirical results and discussion

4.1. Empirical results

Table 7 describes the results from different alternative models in 2013, used to test the sensitivity of the observed results. The following interpretation may focus on Column 9 in Table 7, the other columns being used for comparison. It can be seen that all the important variables have similar signs and statistical significance. These results imply that the high collinearity problem in Table 7 is not a serious issue. If the high collinearity problem really matters in Table 7, it is expected that model will perform worse by introducing the new variables and new interaction terms. The statistical significance, in particular, will be greatly influenced by the high collinearity problem. However, Table 7 shows that these statistical significances perform stably from Column 1 to Column 9, which implies that we can omit the issue of high collinearity here.[6] In fact, it can be seen that most of the important results keep the same sign and significance even when more variables are included (see Table 6). Moreover, the main results are consistent when the model is applied to years 2009 and 2011 as well (see Table A4). Furthermore, to make the results more visualizable, the net result of elasticities for each variable, based on Column 9 in Table 7, are also presented in Fig. 1. The study in Table 7 shows several interesting results.

First, the column 1 in Table 7 shows that there is a quadratic relationship between building density and light car CO_2 road-related emissions, which is presented in the Fig. 2 by plotting the natural logarithm of light car CO_2 emissions on the road against the natural logarithm of build density in 2013.[7]

In particular, Table 7 show that this quadratic relationship between building density and light car CO_2 road-related emissions is stable and statistically significant at the 0.5% threshold across all nine models (see Table 7). The results imply that there is a turning point in the building density: i.e., Column 9 is 10.95 (8.383/(2×0.383)). In this sample in 2013, the average of the log of building density is 6.987 (the maximum value is 8.172; see Table A2). Thus, the net result of the elasticity of building density is positive (3.033), which suggests that a one percent increase in a municipality's building density (<10.95) can result in a 3.033 percent increase in light car CO_2 road-related emissions.

Second, the elasticities of average vehicles owned by low-density houses (LHCR) and the share of low-density houses (LR) are both positive (see Fig. 1) and highly significant at the threshold of 0.1% (see Table 7). This implies that a one percent increase in cars owned by a low-density house may lead to a 1.588 percent increase in CO_2 road-related emissions, while a one percent increase in the lower density housing rate can result in a 1.427 percent increase in CO_2 road-related emissions.

The results are in line with common sense, especially as, according to urban theory, the density of residential housing has a negative relationship with distance from the city centre (Gaigné et al., 2012), which implies that people living in low-density houses need to drive longer distances or use more energy to get to the city centre than do others. Our results are consistent with this hypothesis.

Third, the elasticities for population and urbanization are positive (see Fig. 1) and statistically significant at a threshold of 0.1% (see Table 7), which shows that a one percent increase in population and urbanization will lead to a 0.949 and 2.849 percent increase in light car CO_2 road-related emissions respectively. This result is consistent with the most other findings (e.g.,

[5] Because the predicted value of the dependent variable to the 3rd or more power in Ramsey's test is hard to explain, here Ramsey's test is used to detect the existence of other interactive items in the estimated model. Hence, we only consider the predicted value of the dependent variable to the 2nd power in Ramsey's test, which suggests that the H0 hypothesis (no functional form misspecification) is statistically insignificant at a 10% threshold.

[6] The correlation matrix among independent variables is shown in Table A3.

[7] Data source: SSB, 04861 and 06265, see Table 3. The statistical measure for Fig. 2 can be seen in column 1 of Table 7.

Table 6
Results of the estimated model in 2013.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ols16	ols14	ols13	ols12	ols17	ols18	ols19
po	0.949***** (0.044)	0.941***** (0.043)	0.941***** (0.043)	0.936***** (0.046)	0.937***** (0.047)	0.938***** (0.047)	0.938***** (0.046)
income	11.214**** (3.649)	15.540***** (4.046)	15.530***** (4.037)	18.662**** (5.879)	18.687**** (5.877)	11.764 (7.707)	10.148 (8.016)
hs	1.833* (0.955)	1.918** (0.955)	1.916** (0.954)	1.884* (0.970)	1.884* (0.972)	1.933** (0.972)	1.907* (0.976)
ur	2.849***** (0.498)	2.774***** (0.492)	2.765***** (0.503)	2.738***** (0.511)	2.735***** (0.512)	2.733***** (0.516)	2.729***** (0.517)
ud	−2.976***** (0.444)	−2.922***** (0.435)	−2.913***** (0.444)	−2.886***** (0.453)	−2.883***** (0.453)	−2.876***** (0.456)	−2.880***** (0.458)
ac0_15	1.785**** (0.596)	1.920**** (0.605)	1.923**** (0.614)	2.406** (0.946)	2.451*** (0.936)	2.234** (0.928)	−0.245 (3.208)
ac1619	−0.534*** (0.205)	−0.525** (0.203)	−0.527** (0.206)	−0.382 (0.316)	−0.398 (0.331)	27.210 (24.703)	31.227 (26.407)
ac2034	2.383***** (0.514)	−34.284 (20.927)	−34.226 (20.908)	−44.340 (27.181)	−44.554 (27.114)	−40.584 (26.711)	−36.056 (26.788)
ac3549	−95.664**** (31.022)	−90.039**** (31.311)	−89.980**** (31.292)	−102.640**** (32.924)	−102.493**** (32.981)	−101.277**** (32.256)	−101.052**** (31.572)
ac5069	3.883***** (0.910)	4.087***** (0.921)	4.117***** (1.061)	4.740***** (1.425)	4.760***** (1.417)	4.458**** (1.373)	5.041**** (1.683)
income3549	7.379**** (2.387)	6.957**** (2.406)	6.955**** (2.406)	7.969**** (2.562)	7.962**** (2.565)	7.853**** (2.506)	7.872**** (2.463)
bd	8.385***** (1.508)	8.072***** (1.540)	8.059***** (1.562)	7.973***** (1.606)	7.966***** (1.609)	7.915***** (1.621)	7.972***** (1.610)
bd2	−0.383***** (0.105)	−0.367***** (0.107)	−0.366***** (0.107)	−0.362**** (0.109)	−0.362**** (0.110)	−0.359**** (0.110)	−0.363**** (0.110)
lr	70.152***** (17.131)	69.958***** (17.086)	71.128**** (24.105)	69.331**** (23.892)	75.032** (32.483)	75.441** (32.688)	65.232** (32.705)
lr0_15	10.559**** (3.379)	11.116**** (3.503)	11.124**** (3.538)	10.933**** (3.534)	11.986** (5.503)	12.225** (5.526)	10.136* (5.771)
lr2034	12.277***** (3.118)	12.107***** (3.067)	12.215***** (3.606)	11.753**** (3.640)	12.737** (5.493)	12.756** (5.547)	10.955* (5.640)
lr5069	21.446***** (5.374)	21.020***** (5.250)	21.313**** (6.877)	20.999**** (6.829)	21.907**** (7.492)	21.942**** (7.494)	20.107*** (7.263)
lhcr	1.588***** (0.249)	1.557***** (0.249)	1.553***** (0.251)	1.525***** (0.258)	1.527***** (0.259)	1.528***** (0.262)	1.530***** (0.263)
sv	0.121** (0.054)	0.128** (0.054)	0.127** (0.054)	0.126** (0.054)	0.126** (0.054)	0.132** (0.055)	0.133** (0.056)
income2034		2.812* (1.611)	2.808* (1.610)	3.615* (2.121)	3.636* (2.114)	3.319 (2.082)	2.994 (2.082)
lr3549			0.366 (3.694)	0.234 (3.633)	1.392 (5.867)	1.282 (5.920)	0.074 (6.011)
ac_70				0.365 (0.580)	0.415 (0.600)	0.298 (0.608)	0.569 (0.710)
lr_70					7.035 (30.576)	6.532 (31.027)	−0.758 (32.587)
income1619						−2.128 (1.905)	−2.423 (2.027)

(*continued on next page*)

Table 6 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ols16	ols14	ols13	ols12	ols17	ols18	ols19
income015							1.157 (1.470)
_cons	−159.019***** (47.545)	−213.765***** (51.531)	−213.528***** (51.366)	−249.636***** (69.447)	−249.623***** (69.573)	−161.249* (95.381)	−144.207 (98.392)
N	380	380	380	380	380	380	380
R^2	0.899	0.900	0.900	0.901	0.901	0.901	0.901
adj. R^2	0.894	0.895	0.895	0.894	0.894	0.894	0.894

Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.005$, ***** $p < 0.001$.

Poumanyvong et al. (2012)).

The elasticity of urban density is negative (see Fig. 1) and statistically significant at a threshold of 0.1% (see Table 7), which suggests that a one percent increase in urban density can lead to a 2.976 percent decrease in CO_2 road-related emissions. This result is consistent with other findings (e.g., Lee and Lee (2014); Liddle (2013, 2014)).

Fourth, elasticity of income depends partly on age group 35–49. Both the item of income and the interactive item between income and age structure for the 35–49 group are positive and statistically significant at a threshold of 0.5% (see Table 7). The net effect of income is −0.563 (see Fig. 1). This result implies that a one percent increase in household income can lead to a 0.563 percent decrease in CO_2 road-related emissions, given the average value of age group 35–49.

Fifth, the coefficient of age groups 0–15, 20–34, 50–69 and their interactive items with a low-density housing rate (LR) are positive and statistically significant at a threshold of 0.5% (see Table 7). Given the average LR (−0.118, see Table A2), the elasticities of age groups 0–15, 20–34, 50–69 are 0.539, 0.934 and 1.352 respectively (see Fig. 1). The elasticity of age group 16–19 is negative (−0.534; see Fig. 1) and statistically significant at a threshold of 1% (see Table 7). The elasticity of age group 35–49 depends partly on income level. The coefficient of age group 35–49 is negative, while its interactive item with income is positive, and both coefficients are statistically significant at a threshold of 0.5% (see Table 7). Given the average income (13.051; see Table A2), the elasticity of age group 35–49 is 0.639 (see Fig. 1). The results show that the consumption group with most energy consumption on the road is age group 50–69, followed by groups 20–34, 35–49, 0–15, 70+, and 16–19. These results are consistent with the findings in Lee and Lee (2014), which also show that age group 51–65 emits the most CO_2 road-related emissions.

The interactive items of a low-density housing rate with age groups 0–15, 20–34, 50–69 are positive and significant at a threshold of 0.5% (see Table 7), which suggests that people in age groups 0–15, 20–34 and 50–69 may produce more CO_2 road-related emissions if they move to suburban districts with higher low-density housing rates.

Finally, the elasticity of household size is positive and significant only at a threshold of 10% (see Table 7), which suggests that a larger household size can lead to more CO_2 road-related emissions. This result is consistent with Lee and Lee (2014) and Cao and Yang (2017). The elasticity of the percentage of service sectors is positive and significant at a threshold of 5% (see Table 7), which suggests that an increase in the service sector may lead to more CO_2 road-related emissions. This result is consistent with the findings in Poumanyvong et al. (2012).

4.2. Discussion

The positive elasticity of the log of building density result implies that people living in areas of high building density produce more CO_2 road-related emissions than others living in areas of low building density, which is consistent with the observed facts of the so-called compensatory mechanism hypothesis, suggesting that those living in densely populated urban areas with only a limited need for everyday transport tend to undertake longer journeys in their leisure time as a compensation for their limited access to an outdoor area (Holden and Norland, 2005). At the same time, when building density exceeds the tipping point (here it is 10.95), it can be seen that the increase in building density results in a decrease in CO_2 road-related emissions, which is consistent with the compact city theory (Boussauw et al., 2012; Makido et al., 2012). This theory claims that central and high-density developments, supported by a number of other attributes, are favorable to sustainable energy use. This inverted U-shape verifies the existence of the impact of the economic scale of building density in decreasing environmental impacts. It is similar to the results found by Burgalassi and Luzzati (2015), who claim to have identified the impact of economic scale on the populations of Italian cities. However, it may be difficult to go beyond the tipping point value of the building density because in urban areas it needs to be up to 56954 unit/per square kilometer (or 17 square meters of land per house). These results imply that there may be some limitations on city planners trying to bring downtown areas closer in order to reduce household road transport.

The negative income elasticity in this case differs from that in most research, which shows a positive relationship between income and CO_2 emissions, for example, Poumanyvong et al. (2012). However, this is not surprising because most such research focuses on total CO_2 road-related emissions or transport energy use on the road. Usually, such research may combine three sorts of transport activity (household transport by road, productive transport by road and public transport by road) into one unit, while the present research focuses only on household transport CO_2 road-related emissions. It can readily be seen that light vehicles are the major tools of household transport by road. However, heavy vehicles (such as trucks and tractors) are major forms of productive transport by road, and buses are popular vehicles for public transport by road. Regarding to the urban bus transport systems, the expenditure on bus ticket in Norway for two adults in one year, 14000 kroner in 2019[8], is about 3–4% of household income after tax (in 2013, the minimum household income 357896 kroner (=e^12.788), see Table A2). Thus, from this perspective, it is relative safe to assume that the expenditure on bus can not be a constraint on household income. In addition, the Britain empirical evidence shows that the bus income elasticity is negative, suggesting that the increase in income may lead to the decrease in public transport demand (Paulley et al., 2006). Thus, it is hard to tell the relationship between CO_2 emissions from bus and income, since the

[8] Netsource: https://ruter.no/en/buying-tickets/tickets-and-fares/365-day-tickets

Table 7
Results of the estimated model in 2013.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bd	21.701*****	9.712****	8.026*****	8.612*****	8.738*****	8.199*****	8.194*****	8.257*****	8.385*****
	(5.813)	(3.216)	(2.196)	(1.835)	(1.579)	(1.549)	(1.499)	(1.555)	(1.508)
bd2	−1.543*****	−0.682****	−0.551*****	−0.441*****	−0.442*****	−0.385*****	−0.379*****	−0.388*****	−0.383*****
	(0.404)	(0.223)	(0.152)	(0.130)	(0.112)	(0.107)	(0.104)	(0.108)	(0.105)
Lhcr		3.874*****	0.537****	1.518*****	1.480*****	1.468*****	1.490*****	1.468*****	1.588*****
		(0.225)	(0.188)	(0.241)	(0.250)	(0.251)	(0.253)	(0.253)	(0.249)
Po			0.830*****	0.975*****	0.960*****	0.958*****	0.972*****	0.972*****	0.949*****
			(0.034)	(0.048)	(0.044)	(0.041)	(0.041)	(0.041)	(0.044)
Ur				2.275*****	2.347*****	2.627*****	2.703*****	2.639*****	2.849*****
				(0.392)	(0.430)	(0.459)	(0.467)	(0.467)	(0.498)
Ud				−2.441*****	−2.617*****	−2.893*****	−2.957*****	−2.871*****	−2.976*****
				(0.359)	(0.394)	(0.416)	(0.421)	(0.422)	(0.444)
Lr				1.385*****	1.400*****	31.496****	70.810*****	71.335*****	70.152*****
				(0.320)	(0.318)	(9.957)	(17.814)	(17.752)	(17.131)
Income					10.222****	7.871**	9.141***	9.040***	11.214****
					(3.436)	(3.261)	(3.313)	(3.346)	(3.649)
ac2034					1.232*****	2.035*****	2.541*****	2.392*****	2.383*****
					(0.345)	(0.430)	(0.494)	(0.513)	(0.514)
ac3549					−78.754***	−65.800**	−76.444***	−75.684***	−95.664****
					(28.145)	(27.109)	(27.560)	(27.836)	(31.022)
ac5069					1.398****	3.410*****	4.122*****	3.785*****	3.883*****
					(0.488)	(0.850)	(0.907)	(0.924)	(0.910)
income3549					6.074***	5.086**	5.901***	5.828***	7.379****
					(2.160)	(2.081)	(2.116)	(2.137)	(2.387)
ac0_15						1.366**	2.079****	1.995****	1.785****
						(0.579)	(0.661)	(0.657)	(0.596)
lr2034						7.241****	12.896*****	13.061*****	12.277*****
						(2.407)	(3.280)	(3.268)	(3.118)
lr5069						12.763****	22.750*****	22.710*****	21.446*****
						(4.262)	(5.672)	(5.658)	(5.374)
lr0_15							9.292***	9.459****	10.559****
							(3.346)	(3.333)	(3.379)
ac1619								−0.344*	−0.534***
								(0.200)	(0.205)
Hs									1.833*
									(0.955)
Sv									0.121**
									(0.054)
_cons	−73.844*****	−33.335****	−34.176*****	−26.394*****	−154.271*****	−113.965***	−127.360****	−128.836****	−159.019*****
	(20.852)	(11.593)	(7.972)	(6.800)	(45.011)	(42.696)	(43.087)	(43.530)	(47.545)
N	380	380	380	380	380	380	380	380	380
R^2	0.071	0.524	0.846	0.878	0.886	0.894	0.896	0.897	0.899
adj. R^2	0.066	0.520	0.844	0.875	0.883	0.889	0.891	0.892	0.894

Standard errors in parentheses.
* $p < 0.1$,** $p < 0.05$,*** $p < 0.01$,**** $p < 0.005$,***** $p < 0.001$.

bus transport system is usually funded by government and operated with regular routes and regular schedule. Regarding to productive transport by road, this is highly organized by private companies, so to some extent it cannot be a constraint on household consumption. Moreover, some evidence from UK also show that the elasticity of diesel demand in the road freight sector with respect to income is positive, suggesting that the increase in income can lead to more CO_2 emissions from freight sectors (Wadud, 2016). Thus, it is possible to have positive income elasticity when the freight transport on road is considered. In contrast, light vehicles are choices that result from

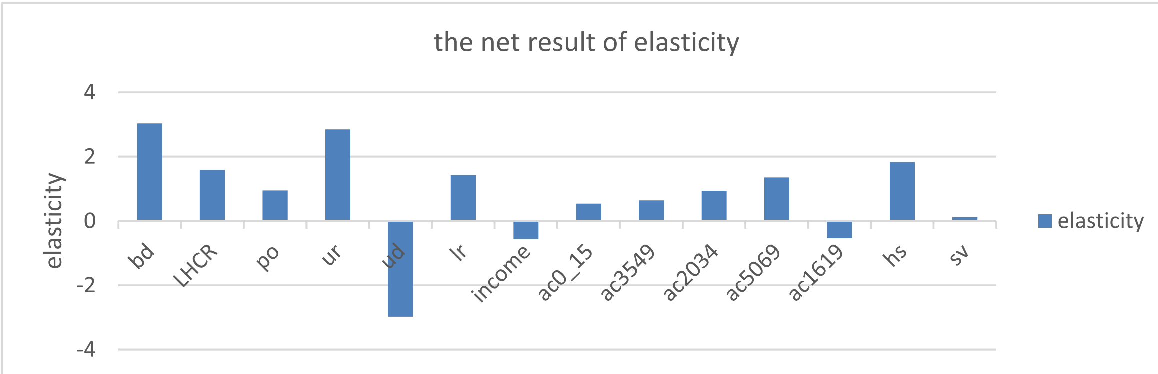

Fig. 1. The net result of elasticities.

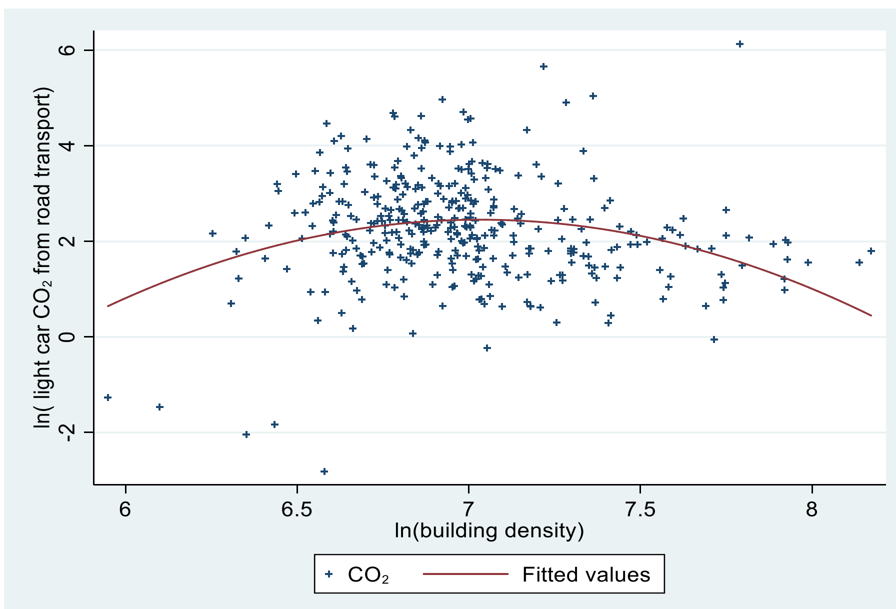

Fig. 2. The relationship between CO_2 emissions and building density.

household consumption. Indeed, there is a direct connection between the choice of light vehicles and household income. Thus, Erdem et al. (2010) showed that wealthy purchasers have a greater willingness to pay for HEVs (hybrid electric vehicles). Also, Pablo-Romero et al. (2017) verified empirically that a Kuznets curve exists between household transport energy use and gross value added per capita for data covering twenty-seven EU countries in the period 1995–2009, which suggests that there is a tipping point for household transport energy use. This implies that it is possible for high-income countries to have a negative relationship when income is above the tipping point value.

Moreover, in Norway certain specific facts may explain net negative income elasticity. First, it is worth noting that the dependent variable here is only CO_2 road-related emissions, which reflects the behavior in terms of road energy consumption. In fact, plane travel may be a competitive option for a household's long-distance leisure-time transport, with the growth in household incomes. According to SSB, there were 16.087 million airport passengers in the third quarter of 2018 in Norway, an increase of 6.3% since 2014. Domestic aviation accounts for 52.58%, with an increase of 4.4%, while international aviation amounts to 47.4%, with an increase of 8.4% since 2014 (Statistics Norway, 2019c). Moreover, it can be seen that there is a negative relationship between household income and average miles per passenger car in Norway, which is presented in the following Fig. 3.

By plotting the logarithm of median household income against the average miles per passenger car for each municipality in 2013, [9] the Fig. 3 shows that an increase in household incomes may co-occur with a decrease in average miles per passenger car, suggesting a negative relationship between household incomes and CO_2 emissions from household road travel.

Based on these two facts, it is reasonable to assume that households in Norway choose more air transport than land transport for their long-distance journeys with the growth in household income. Other explanations may be that households may choose more efficient cars with increases in household incomes. In fact, this assumption has been verified by some researchers, who claim that wealthy purchasers express a stronger willingness to pay for HEVs (Erdem et al., 2010). According to SSB, total private vehicles were 2,768,864 in 2018, an increase of 9.2% in the period

[9] Data from SSB, 08741: Road traffic volumes average per vehicle. The R-squared for this bivariate regression in Fig. 2 is 0.0137, with a p-value of 0.0001.

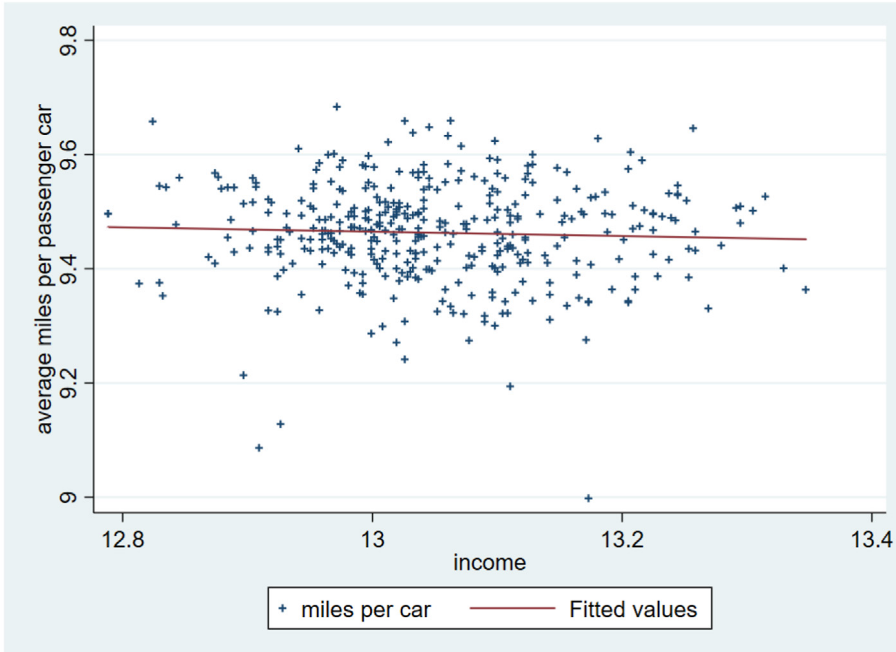

Fig. 3. The relationship between household income and average miles per passenger car.

2013–2018, while the percentage of electric cars increased by 999.3% in the period 2013–2018 (Statistics Norway, 2019a). There were 25960 hybrid cars in 2018, 50.8% more than in 2017 (Lund, 2019). Therefore, based on these three facts, it is reasonable to suggest that net elasticity of household income with respect to CO_2 emissions from household transport by road is negative. Moreover, our results are consistent with the findings in Chatterton et al. (2018), who found a negative relationship between household income and the percentage of income spent on road fuel in the UK.

Although some research has found a positive effect of income on the environment (Liddle, 2004, 2011; Liddle and Lung, 2010; Poumanyvong et al., 2012), other results differ. For example, Handy et al. (2005) found that changes in household income have no effect on changing driving habits. Lee and Lee (2014) found incomes below US$20,000 and between US$20,000–35,000 to have a negative effect on household CO_2 road-related emissions, while incomes of US$55,000–80,000 and over US$80,000 have a positive effect. Our results are different from these, for two possible reasons. First, most of this research focuses on transport emissions on the road (e.g. Poumanyvong et al. (2012)), while this paper only focuses on light car road-related emissions, which is only one part of road transport. Second, the differences may be due to the different model settings. As we have mentioned, most research does not take into account the indirect effects of age structures and the potential effects of urban forms. These assumptions may be questionable and can lead to different results. In fact, our results can obtain the same positive effect of income if we exclude the interactive item between income and age group 35–49. However, the result may be questionable.

As expected, the coefficient of the interactive item between income and age group 35–49 is positive and significant at a threshold of 0.5%, which implies that an increase in household income can lead to more CO_2 road-related emissions. This also implies that the traffic behavior pattern of age group 35–49 is significantly changed by the increase in household income, while the road traffic behavior patterns of other age groups (0–15, 16–19, 20–34, 50–69 and 70+), having implicit zero coefficients, are not changed significantly by such increases. These results seem reasonable for three reasons. First, it should be noted that income here is median household income. Regarding age group 6–16, it is mandatory for them to attend school. Regarding the age group 16–19, it is common to treat them as adolescents (Sivertsen et al., 2015). They were reported to have graduated from upper secondary school at a rate of 73% in 2017 (Gjerstad, 2017). These facts imply that most of age group 0–19 are school students in Norway. Their daily travel patterns are simple and fixed, while their leisure-time travel may be determined by their parents or be met by public transport. Therefore, it is reasonable to suggest that their driving behavior patterns on the road are not influenced by median household incomes. Moreover, regarding age group 20–34, it is interesting to see that the average age at first birth in Norway was between 28 and 29 for women and between 30 and 31 for men in the period 2007–2017 (Statistics Norway, 2019b). The average age at marriage was 34 for men and 31 for women in the same period.[10] Therefore, it is reasonable to argue most of age group 20–34 are single and might live in small house. If they have children, they will be around age three and have limited social activities. Moreover, it has been found that there is a tendency for young adults to defer obtaining a driving license and depending more on public transport in urban areas (Hjorthol, 2016). Thus, our results indicating that their road transport behavior patterns may not change significantly by an increase of the median household income are consistent with these facts. Besides, compared with the median household income, age groups 50–69 and 70+ are relatively high-income households with small household sizes. In particular, although the retirement age in Norway is 67, the employment rate for old people (<67) is not 100%. According to SSB in 2018, the employment rate for people age 55–66 is about 64%, which implies 36% of the old people (55–66) are not in labor market during this period. Moreover, some old people (>67) are still working since the employment rate for old people (age 67–74) is 7.8%.[11] These two facts imply that there is a smooth transition for some

[10] SSB: 05742: Average age at marriage, by sex. Marriages between different sexes, 1974–2017.

[11] Data come from Table 03779: Population (1 000 persons), by age, main activity, contents and year.

old working people to be a retiree. At the same time, if the old people quit from labor market before 67, it is reasonable to assume there will have no significant change of living style among them before 70 since the life expectancy in 2013 was 81.75 (Statistics Norway, 2018). Therefore, their traffic behavior patterns on the road may be fixed and remain unchanged by increases in median household incomes. Furthermore, according to Morrow-Jones and Wenning (2005), there is an implicit housing hierarchy in which low- and moderate-income tenants move into more comfortable quarters, while the wealthier tenants save to become first-time homebuyers, later trading up to bigger and better homes. Age group 35–49 are the median age group among the six groups, which is also the period in which households tend to upgrade from smaller houses to larger and better houses. Therefore, it is not surprising to see that this age group, 35–49, is constrained by household incomes. These groups usually have large household sizes with children who are more active and liable to have more road transport activities, such as participation in a friend's birthday party or different interest clubs after class. Hence, the change in household incomes may greatly influence the traffic behavior patterns of group 35–49 on the road.

Taken together, the findings of this study have some policy implications when it comes to reducing CO_2 road-related emissions in Norway. First, the verification of a compensatory mechanism hypothesis suggests that people living in areas of higher building density have more CO_2 road-related emissions than those living in areas with lower building-density. It also suggests that plans to bring the city center closer in order to decrease household CO_2 road-related emissions is not a feasible solution. However, as the maximum value of urban density in Norwegian municipalities was 46.98 per hectare in 2013 (see Table A2), which is relatively small compared to data from other countries,[12] a compact city with a higher population density is much to be preferred. Second, it was found that an average low-density housing rate of 0.88 and its elasticity is positive, which suggests that an increase in people living in low-density housing may lead to more CO_2 road-related emissions. This implies that restricting the development of low-density housing to decrease household CO_2 road-related emissions might be a feasible city plan in Norway. Third, Fig. 1 indicates that all age groups except 16–19 have a positive impact on CO_2 road-related emissions. There is a significant change in energy consumption patterns between the 16–19 and 20–34 groups. From the perspective of decarbonization, policy should encourage the 16–19 group to use public transport exclusively. For other age structures, using more energy-efficient vehicles should be encouraged. Furthermore, our analysis is currently based on traditional modes of energy consumption, namely petrol and diesel. The results may have some limitations due to the rapid development of renewable energy technology (such as biogas, solar and electric battery) in the transport sector (Cong et al., 2017; Marchi et al., 2018). It is not clear how people of different ages react to the new emerging vehicles. The preference for such vehicles may differ among different age groups, which may have different implications for decarbonization. These topics are interesting but go beyond the scope of this study; they can therefore be left for the future.

5. Conclusion

This article has investigated the influence of age structure on household road transport CO_2 emissions by using an extended STIRPAT model with 2009, 2011, and 2013 data from 380 Norwegian municipalities. After controlling for population, household income, age structures, household size and different urban forms (urbanization, urban density, housing type and building density), the paper reveals that the highest group for CO_2 emissions is 50–69, followed by 20–34 and 35–49. Moreover, the latter age group should be given greater attention because its road transport activities are significantly influenced by household incomes. This paper also reveals the existence of an inverted U-shape relationship between household CO_2 road-related emissions and building density. However, there might be some limitations for city planners trying to reduce household CO_2 road-related emissions by bringing downtown areas closer. Moreover, the paper also verifies the so-called compensatory mechanism hypothesis (Holden and Norland, 2005), which shows the positive effects of building densities. However, the coefficient of low-density housing is positive and significant, which implies that the private gardens of low-density housing might not be the explanation for the so-called compensatory mechanism hypothesis.

Nevertheless, some limitations of this study should be mentioned. Predictors for explaining the variation in household CO_2 road-related emissions are limited and by no means comprehensive. At the same time, the results have been obtained in the context of Norway specifically, a long, extended country with many small municipalities and low urban population densities. Moreover, the results might only apply to the short-term effects, as they are mainly based on data for 2013. Nevertheless, the study provides a foundation for further investigation of the impact of demographic changes on CO_2 road-related emissions in urban areas and suggests that low-density housing with a private garden is not the cause of the so-called compensatory mechanism hypothesis. Whether people living in high building density areas produce more CO_2 road-related emissions than those living in low building density areas is still an interesting question worth further investigation.

Table A1
Summary Statistics of Explanatory Variables in 2009–2013

Variable	Obs	Mean	Std. Dev.	Min	Max
co1	1140	2.26	1.11	−2.81	6.17
po	1140	8.64	1.10	6.12	13.34
income	1139	12.98	0.12	12.55	13.35
hs	1139	0.84	0.06	0.55	1.03
ur	1140	−0.66	0.48	−2.26	0.00
ud	1140	6.92	0.42	5.89	8.45
ac0_15	1140	−1.63	0.11	−2.03	−1.34
ac1619	1140	−2.90	0.11	−3.32	−2.21
ac2034	1140	−1.81	0.13	−2.23	−1.27
ac3549	1140	−1.58	0.09	−1.89	−1.31
ac5069	1140	−1.39	0.10	−1.72	−1.05
bd	1140	6.87	0.36	5.71	8.17
lr	1140	−0.11	0.12	−1.42	0.00
lhcr	1140	0.25	0.20	−0.79	1.25
sv	1139	−1.30	0.47	−3.02	−0.07

Table A2
Summary Statistics of explanatory Variables in 2013

Variable	Obs	Mean	Std. Dev.	Min	Max
co1	380	2.267	1.106	−2.813	6.130
po	380	8.659	1.109	6.221	13.344
income	380	13.051	0.104	12.788	13.347
hs	380	0.834	0.059	0.628	1.023
ur	380	−0.642	0.470	−2.260	−0.011
ud	380	7.048	0.391	6.079	8.455
ac0_15	380	−1.655	0.119	−2.034	−1.360
ac1619	380	−2.910	0.112	−3.281	−2.255
ac2034	380	−1.783	0.129	−2.201	−1.265
ac3549	380	−1.596	0.088	−1.888	−1.332
ac5069	380	−1.369	0.104	−1.679	−1.048
bd	380	6.987	0.344	5.949	8.172
lr	380	−0.118	0.116	−1.422	−0.009
lhcr	380	0.287	0.198	−0.423	1.246
sv	380	−1.341	0.470	−3.022	−0.069

[12] The mean of urban density in OECD/developed countries in 1995 is 52.6 per hectare (Liddle, 2013, p. 21).

Table A3
The Correlation Matrix among Independent Variables

	po	income	hs	ur	ud	ac0_15	ac1619	ac2034	ac3549	ac5069	ac_70	bd	lr	lhcr	Sv
Po	1														
income	0.3146	1													
Hs	−0.0675	0.7472	1												
Ur	0.5825	0.2322	−0.1234	1											
Ud	0.7394	0.3727	−0.0257	0.7252	1										
ac0_15	0.3772	0.8077	0.6981	0.307	0.4222	1									
ac1619	−0.0519	0.189	0.3665	0.0472	0.0616	0.1914	1								
ac2034	0.5369	0.333	0.1244	0.4815	0.5468	0.5048	−0.0515	1							
ac3549	0.502	0.3431	0.0096	0.4834	0.5082	0.3971	−0.0755	0.2828	1						
ac5069	−0.4929	−0.6036	−0.4573	−0.445	−0.5487	−0.7957	−0.1961	−0.7407	−0.5271	1					
ac_70	−0.5788	−0.6576	−0.3349	−0.5312	−0.6413	−0.7666	−0.0995	−0.6886	−0.6827	0.7312	1				
Bd	−0.1488	−0.1543	−0.0589	−0.685	−0.0421	−0.2065	−0.0558	−0.1796	−0.271	0.2096	0.2531	1			
Lr	−0.6613	−0.0196	0.2996	−0.5024	−0.6516	−0.0837	0.158	−0.4935	−0.3227	0.3603	0.3421	−0.017	1		
Lhcr	0.7289	0.4913	0.2138	0.3156	0.5037	0.4953	−0.0413	0.3694	0.5165	−0.4739	−0.5732	−0.1186	−0.4746	1	
Sv	0.4162	−0.2194	−0.3366	0.313	0.2199	−0.0658	0.0169	0.2449	0.0962	−0.0941	−0.0699	−0.1444	−0.3464	0.062	1

Table A4
Results of the Estimated Model in 2013, 2011, 2009

	(1)	(2)	(3)
	ols2013	ols2011	ols2009
Po	0.949*****	0.941*****	0.937*****
	(0.044)	(0.047)	(0.052)
income	11.214****	12.966*****	9.758****
	(3.649)	(3.779)	(3.219)
hs	1.833*	2.338**	0.640
	(0.955)	(1.049)	(0.792)
ur	2.849*****	2.670*****	2.508*****
	(0.498)	(0.504)	(0.466)
ud	−2.976*****	−2.886*****	−2.770*****
	(0.444)	(0.457)	(0.441)
ac0_15	1.785****	1.513**	1.220**
	(0.596)	(0.680)	(0.554)
ac1619	−0.534***	−0.260	0.334
	(0.205)	(0.232)	(0.288)
ac2034	2.383*****	2.063*****	1.727*****
	(0.514)	(0.497)	(0.443)
ac3549	−95.664****	−111.777*****	−79.692****
	(31.022)	(32.466)	(26.938)
ac5069	3.883*****	3.713*****	2.861*****
	(0.910)	(0.855)	(0.747)
income3549	7.379****	8.687*****	6.241****
	(2.387)	(2.510)	(2.090)
Bd	8.385*****	6.068*****	6.672*****
	(1.508)	(1.728)	(1.873)
bd2	−0.383*****	−0.243*	−0.293**
	(0.105)	(0.128)	(0.133)
Lr	70.152*****	48.553****	45.281****
	(17.131)	(15.274)	(14.612)
lr0_15	10.559****	6.691**	7.544**
	(3.379)	(2.997)	(2.956)
lr2034	12.277*****	8.465****	7.336***
	(3.118)	(2.775)	(2.665)
lr5069	21.446*****	15.368****	13.224***
	(5.374)	(4.962)	(4.756)
lhcr	1.588*****	1.526*****	1.497*****
	(0.249)	(0.261)	(0.218)
Sv	0.121**	0.138**	0.111*
	(0.054)	(0.057)	(0.058)
_cons	−159.019*****	−172.579*****	−132.107****
	(47.545)	(48.312)	(41.628)
N	380	379	380
R^2	0.899	0.893	0.887
Adj. R^2	0.894	0.887	0.881

Standard errors in parentheses.
* $p < 0.1$,** $p < 0.05$,*** $p < 0.01$,**** $p < 0.005$,***** $p < 0.001$.

References

Bardazzi, R., Pazienza, M.G., 2018. Ageing and private transport fuel expenditure: do generations matter? Energy Pol. 117, 396–405.

Boussauw, K., Neutens, T., Witlox, F., 2012. Relationship between spatial proximity and travel-to-work distance: the effect of the compact city. Reg. Stud. 46 (6), 687–706.

Burgalassi, D., Luzzati, T., 2015. Urban spatial structure and environmental emissions: a survey of the literature and some empirical evidence for Italian NUTS 3 regions. Cities 49, 134–148.

Cao, X., Yang, W., 2017. Examining the effects of the built environment and residential self-selection on commuting trips and the related CO2 emissions: an empirical study in Guangzhou, China. Transport. Res. Transport Environ. 52, 480–494.

Chatterton, T., Anable, J., Cairns, S., Wilson, R.E., 2018. Financial Implications of Car Ownership and Use: a distributional analysis based on observed spatial variance considering income and domestic energy costs. Transport Pol. 65, 30–39.

Cong, R.-G., Caro, D., Thomsen, M., 2017. Is it beneficial to use biogas in the Danish transport sector? – an environmental-economic analysis. J. Clean. Prod. 165, 1025–1035.

Dietz, T., Rosa, E.A., 1997. Eff. Popul. Affluence on CO2 ?emiss. 94 (1), 175–179.

Ehrlich, P.R., Holdren, J.P., 1971. Impact of population growth. Science 171 (3977), 1212–1217.

Erdem, C., Şentürk, İ., Şimşek, T., 2010. Identifying the factors affecting the willingness to pay for fuel-efficient vehicles in Turkey: a case of hybrids. Energy Pol. 38 (6), 3038–3043.

European Commission, 2017. European territorial treends: facts and prospects for cities and regions. URL, accessed 11.15.2019. https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/european-territorial-trends-facts-and-prospects-cities-and-regions-ed-2017/.
European Parliament, 2019. CO2 emissions from cars: facts and figures. URL, accessed 11.15.2019. https://www.europarl.europa.eu/news/en/headlines/society/20190313STO31218/co2-emissions-from-cars-facts-and-figures-info-graphics/.
Fan, Y., Liu, L.-C., Wu, G., Wei, Y.-M., 2006. Analyzing impact factors of CO2 emissions using the STIRPAT model. Environ. Impact Assess. Rev. 26 (4), 377–395.
Gaigné, C., Riou, S., Thisse, J.F., 2012. Are compact cities environmentally friendly? J. Urban Econ. 72 (2–3), 123–136.
Gheorghiu, A., Delhomme, P., 2018. For which types of trips do French drivers carpool? Motivations underlying carpooling for different types of trips. Transport. Res. Pol. Pract. 113, 460–475.
Gjerstad, S., . Aldri har så mange fullført videregående skole. https://www.tv2.no/a/9325873/. URL, accessed 11.15.2019. .
Handy, S., Cao, X., Mokhtarian, P., 2005. Correlation or causality between the built environment and travel behavior? Evidence from Northern California. Transport. Res. Transport Environ. 10 (6), 427–444.
Hasanov, F.J., Bulut, C., Suleymanov, E., 2016. Do population age groups matter in the energy use of the oil-exporting countries? Econ. Modell. 54, 82–99.
Hasanov, F.J., Mikayilov, J.I., 2017. The impact of age groups on consumption of residential electricity in Azerbaijan. Commun. Post Commun. Stud. 50 (4), 339–351.
Hjorthol, R., 2016. Decreasing popularity of the car? Changes in driving licence and access to a car among young adults over a 25-year period in Norway. J. Transport Geogr. 51, 140–146.
Holden, E., Norland, I.T., 2005. Three challenges for the compact city as a sustainable urban form: household consumption of energy and transport in eight residential areas in the greater oslo region. Urban Stud. 42 (12), 2145–2166.
Lee, S., Lee, B., 2014. The influence of urban form on GHG emissions in the US household sector. Energy Pol. 68, 534–549.
Lee, Y., Montgomery, C.A., Kline, J.D., 2016. The influence of age-specific migration on housing growth in the rural Midwest (USA). Landsc. Urban Plann. 148, 68–79.
Leon, C.J., Arana, J.E., Aleman, A.H., 2014. CO2 Emissions and tourism in developed and less developed countries. Appl. Econ. Lett. 21 (16), 1169–1173.
Liddle, B., 2004. Demographic dynamics and per capita environmental impact: using panel regressions and household decompositions to examine population and transport. Popul. Environ. 26 (1), 23–39.
Liddle, B., 2011. Consumption-driven environmental impact and age structure change in OECD countries: a cointegration-STIRPAT analysis. Demogr. Res. 24, 749–770.
Liddle, B., 2013. Urban density and climate change: a STIRPAT analysis using city-level data. J. Transport Geogr. 28, 22–29.
Liddle, B., 2014. Impact of population, age structure, and urbanization on carbon emissions/energy consumption: evidence from macro-level, cross-country analyses. Popul. Environ. 35 (3), 286–304.
Liddle, B., Lung, S., 2010. Age-structure, urbanization, and climate change in developed countries: revisiting STIRPAT for disaggregated population and consumption-related environmental impacts. Popul. Environ. 31 (5), 317–343.
Liu, Y., Huang, L., Kaloudis, A., Støre-Valen, M., 2017. Does urbanization lead to less energy use on road transport? Evidence from municipalities in Norway. Transport. Res. Transport Environ. 57, 363–377.
Lugauer, S., Jensen, R., Sadler, C., 2014. An estimate of the age distribution's effect on carbon dioxide emissions. Econ. Inq. 52 (2), 914–929.
Lund, V., 2019. Elbiler Og Hybrider Suser Fram.
Makido, Y., Dhakal, S., Yamagata, Y., 2012. Relationship between urban form and CO2 emissions: evidence from fifty Japanese cities. Urban Clim. 2, 55–67.
Marchi, M., Niccolucci, V., Pulselli, R.M., Marchettini, N., 2018. Environmental policies for GHG emissions reduction and energy transition in the medieval historic centre of Siena (Italy): the role of solar energy. J. Clean. Prod. 185, 829–840.
Martinez-Zarzoso, I., Maruotti, A., 2011. The impact of urbanization on CO2 emissions: evidence from developing countries. Ecol. Econ. 70 (7), 1344–1353.
Menz, T., Kuhling, J., 2011. Population aging and environmental quality in OECD countries: evidence from sulfur dioxide emissions data. Popul. Environ. 33 (1), 55–79.
Menz, T., Welsch, H., 2012. Population aging and carbon emissions in OECD countries: accounting for life-cycle and cohort effects. Energy Econ. 34 (3), 842–849.
Modigliani, F., 1966. The life cycle hypothesis OF saving, the demand for wealth and the supply OF capital. Soc. Res. 33 (2), 160–217.
Morrow-Jones, H.A., Wenning, M.V., 2005. The housing ladder, the housing life-cycle and the housing life-course: upward and downward movement among repeat home-buyers in a US metropolitan housing market. Urban Stud. 42 (10), 1739–1754.
Okada, A., 2012. Is an increased elderly population related to decreased CO2 emissions from road transportation? Energy Pol. 45, 286–292.
Ota, T., Kakinaka, M., Kotani, K., 2018. Demographic effects on residential electricity and city gas consumption in the aging society of Japan. Energy Pol. 115, 503–513.
Pablo-Romero, M.P., Cruz, L., Barata, E., 2017. Testing the transport energy-environmental Kuznets curve hypothesis in the EU27 countries. Energy Econ. 62, 257–269.
Paulley, N., Balcombe, R., Mackett, R., Titheridge, H., Preston, J., Wardman, M., Shires, J., White, P., 2006. The demand for public transport: the effects of fares, quality of service, income and car ownership. Transport Pol. 13 (4), 295–306.
Poumanyvong, P., Kaneko, S., Dhakal, S., 2012. Impacts of urbanization on national transport and road energy use: evidence from low, middle and high income countries. Energy Pol. 46, 268–277.
Pulselli, R.M., Marchi, M., Neri, E., Marchettini, N., Bastianoni, S., 2019. Carbon accounting framework for decarbonisation of European city neighbourhoods. J. Clean. Prod. 208, 850–868.
Roberts, T.D., 2014. Intergenerational transfers in US county-level CO2 emissions. Popul. Environ. 35 (4), 365–390, 2007.
Sivertsen, B., Skogen, J.C., Jakobsen, R., Hysing, M., 2015. Sleep and use of alcohol and drug in adolescence. A large population-based study of Norwegian adolescents aged 16 to 19 years. Drug Alcohol Depend. 149, 180–186.
Statistics Norway, 2017. Fylkesvis kommunekatalog 2017. URL, accessed 11.15.2019. https://www.ssb.no/offentlig-sektor/kommunekatalog/kommunekatalog-2017/fylkesvis-kommunekatalog-2017/.
Statistics Norway, 2018. More similar life expectancy for men and women. URL, accessed 11.15.2019. https://www.ssb.no/en/befolkning/artikler-og-publikasjoner/more-similar-life-expectancy-for-men-and-women/.
Statistics Norway, 2019a. Bilparken. URL, accessed 11.15.2019. https://www.ssb.no/transport-og-reiseliv/statistikker/bilreg/.
Statistics Norway, 2019b. Fødte. URL, accessed 11.15.2019. https://www.ssb.no/befolkning/statistikker/fodte/.
Statistics Norway, 2019c. Lufttransport. URL, accessed 11.15.2019. https://www.ssb.no/transport-og-reiseliv/statistikker/flytrafikk/.
Vélez-Henao, J.-A., Font Vivanco, D., Hernández-Riveros, J.-A., 2019. Technological change and the rebound effect in the STIRPAT model: a critical view. Energy Pol. 129, 1372–1381.
Wadud, Z., 2016. Diesel demand in the road freight sector in the UK: estimates for different vehicle types. Appl. Energy 165, 849–857.
Wang, Y.A., Kang, Y.Q., Wang, J., Xu, L.N., 2017. Panel estimation for the impacts of population-related factors on CO2 emissions: a regional analysis in China. Ecol. Indicat. 78, 322–330.
Yang, Y.Y., Zhao, T., Wang, Y., Shi, Z., 2015a. Research on impacts of population-related factors on carbon emissions in Beijing from 1984 to 2012. Environ. Impact Assess. Rev. 55, 45–53.
Yang, W., Li, T., Cao, X., 2015b. Examining the impacts of socio-economic factors, urban form and transportation development on CO2 emissions from transportation in China: a panel data analysis of China's provinces. Habitat Int. 49, 212–220.
Yang, Y., Wang, C., Liu, W., 2018. Urban daily travel carbon emissions accounting and mitigation potential analysis using surveyed individual data. J. Clean. Prod. 192, 821–834.
York, R., 2007. Demographic trends and energy consumption in European Union Nations, 1960–2025. Soc. Sci. Res. 36 (3), 855–872.
Zhang, C.G., Tan, Z., 2016. The relationships between population factors and China's carbon emissions: does population aging matter? Renew. Sustain. Energy Rev. 65, 1018–1025.
Zhang, N., Yu, K.R., Chen, Z.F., 2017. How does urbanization affect carbon dioxide emissions? A cross-country panel data analysis. Energy Pol. 107, 678–687.
Zhang, Z.Y., Hao, Y., Lu, Z.N., Deng, Y.X., 2018. How does demographic structure affect environmental quality? Empirical evidence from China. Resour. Conserv. Recycl. 133, 242–249.
Zhou, Y., Liu, Y.S., 2016. Does population have a larger impact on carbon dioxide emissions than income? Evidence from a cross-regional panel analysis in China. Appl. Energy 180, 800–809.