

Are We Willing to Relocate with the Future Introduction of Flying Cars? An Exploratory Empirical Analysis of Public Perceptions in the United States

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Flying cars, a new transportation mode capable of operating on both land and air, are expected to be introduced in the existing traffic fleet over the next decade or so. Due to their potential in offering flexible mobility patterns, as well as shorter and more reliable travel times, flying cars are anticipated to bring forth significant changes in the urban transportation network. Even though the launch of flying cars is expected relatively soon, potential effects of this new transportation mode on public preferences towards residence location, due to anticipated improvements in mobility access, have not been explored to date. This paper aims to analyse whether a residence relocation trend (from urban to rural areas, or vice versa) is imminent if flying cars are introduced in the not so distant future. In this respect, an online survey was conducted where 584 individuals from the United States participated. The data from this survey are then statistically analysed through correlated grouped random parameters bivariate and univariate probit models, which are capable of accounting for several layers of unobserved heterogeneity. The analysis reveals that various socio-demographic characteristics of the individuals, and their opinions towards the perceived benefits and challenges of flying cars affect public opinions towards considering residence relocation due to the future introduction of flying cars. Although the existing knowledge regarding the operation of flying cars is currently limited, the findings from this study can provide insights into the travel demand, land use, urban and regional planning related challenges likely to be faced in urban and rural areas by policymakers, urban planners, and manufacturing companies, upon the introduction of flying cars.

Keywords: Residence relocation; Flying cars; Bivariate probit models; Binary probit models; Urban Air Mobility; Advanced Air Mobility; Unobserved heterogeneity

1. Introduction

Over the last century, the impact of cutting-edge innovations on the modern transportation system, as we know it, has been revolutionary. The door-to-door transportation capability of automobile technology coupled with a significant reduction in travel times, at a household level, have transformed the overall structure of cities and urban areas. The ubiquitous access to flexible

mobility offered by the automobile, in conjunction with the rapidly expanding road network triggered a wave of suburban migration throughout the United States in the sixties (Melosi, 2004), which profoundly influenced subsequent urban and regional planning as well as travel demand management. In a similar fashion, past research has demonstrated the effect of having access to a public transit on the residence relocation choice of the passengers (Scheiner, 2006; Cervero and Day, 2008; Klinger and Lanzendorf, 2016; Liu et al., 2016; Lin et al., 2018; Ardeshiri and Vij, 2019). Interestingly, a common contributing factor in both of these cases is the increased mobility offered by the newly introduced transportation modes, automobile and public transit. In this context, the last couple of decades have seen a steady rise in the demand of automobiles as well as expansion of existing transportation infrastructure systems. However, with the scope of the latter being diminished in recent years, the technological advancements coupled with a strong push towards the development of efficient transportation technologies have led to the introduction of ridesharing services, and the future deployment of autonomous vehicles (AVs). A combination of both ridesharing and autonomous technologies has also gained significant momentum with Waymo leading the charge (Korosec, 2019). Significant number of studies have demonstrated the advantages of AVs over traditional automobiles in terms of reduced and more reliable travel times, reduction in traffic congestion, overall reduction in commuting cost (Fagnant and Kockelman, 2014; Childress et al., 2015; Fagnant and Kockelman, 2015; Fagnant and Kockelman, 2016; Talebpour and Mahmassani, 2016; Ye and Yamamoto, 2018), as well as safety benefits (Papadoulis et al., 2019; Viridi et al., 2019; Ye and Yamamoto, 2019), such as fewer and less severe crashes. In this context, it is important to note that the potential benefits of AVs are likely to be realized only in certain deployment scenarios, specifically, through ridesharing or carsharing services. If AVs replace privately owned vehicles, the ease of travelling offered by AVs may

induce increased propensity among AV owners towards making additional trips. This may translate to increase in vehicle miles travelled (VMT), which in turn, may increase congestion in the ground transportation network (Fagnant and Kockelman, 2014; Correia and van Arem, 2016; Auld et al., 2017, 2018; Bahamonde-Birke et al., 2018; Hensher, 2018; Soteropoulos et al., 2019). In this context, despite the potential of causing increased congestion in certain usage scenarios, the aforementioned benefits and the additional flexibility in mobility patterns offered by AVs are anticipated to affect residential choices of potential users (Zakharenko, 2016; Harb et al., 2018; Carrese et al., 2019; Gelauff et al., 2019; Javanshour et al., 2019).

The strive towards achieving maximum mobility benefits combined with contemporary technological advancements have paved the way for a new transportation mode, namely the flying car. While the scope of expanding the existing ground-based two dimensional transportation infrastructure is becoming restrictive, flying cars have the capability of utilizing not only the existing ground-based infrastructure, but also the third available dimension, i.e., the air. Flying cars are expected to travel up to 500 miles in a single trip at a cruising speed of 200mph in the air while carrying two to four passengers. In addition, their operation on the ground will closely resemble that of conventional privately owned automobiles without requiring any additional infrastructure requirements. Recent resources anticipate that flying cars are going join the existing traffic in this decade (Becker, 2017; Oppitz and Tomsu, 2018). A number of startups (Terrafugia, AeroMobil and PAL-V) have developed working prototypes of flying cars, and are currently accepting pre-orders for future sales. Traditional automotive and aircraft manufacturing companies (Audi, Aston Martin, Airbus, Rolls-Royce, and Boeing) have also exhibited their flying car concepts, and announced plans to commercially launch sales of flying cars in the near future (Muioio, 2017; Airbus, 2018; Rocco, 2018a; Rocco, 2018b; Rolls-Royce, 2018; Porter, 2019). It

should be noted that the aforementioned operational characteristics, and anticipated mobility benefits of flying cars primarily reflect the views of the manufacturers and future service providers. Further investigation by third-party entities such as research organizations, governmental or legislative bodies and transport communities to accurately determine such characteristics as well as potential benefits and caveats is warranted.

In another recent development NASA has formally announced their plans to embrace “Urban Air Mobility (UAM)”, which is defined as an air passenger and small cargo transportation system in an urban setting (NASA, 2017). This announcement was closely followed by another comprehensive plan to collaborate with potential industry partners to develop manufacturing and operational standards, safe and secure airspace management standards, and necessary regulatory framework with anticipated support from Federal Aviation Administration (FAA) (NASA, 2018b; NASA, 2018a). Additionally, a few recent studies have conducted introductory analysis on adoption and use case scenarios for urban air mobility (Fu et al., 2019; Al Haddad et al., 2020). Fu et al. (2019) concluded that younger individuals, and individuals with high income level would be among the early adopters of urban air mobility and flying taxis. Al Haddad et al. (2020) collected responses from 221 respondents in a Stated Preference survey, and their statistical analysis showed that tech-savviness, and affinity towards automation had a positive impact towards early adoption of urban air mobility. On the other hand, security, safety, and data privacy concerns were found to have negative impact towards adopting urban air mobility.

It should be noted that prior studies have revealed people’s preference towards suburban living while accepting trade-offs in terms of long travel distances (Melosi, 2004; Palm et al., 2014; Scheiner, 2018). In contrast to the latter, another observation in recent years is people’s tendency to move towards cities where travel distance and associated cost is lower, amenities are prevalent,

whereas housing cost is higher (Wachs, 2013; Scheiner, 2018). Since the anticipated operational characteristics of flying cars are going to outclass the existing transportation modes in terms of shorter and more reliable travel times with true door-to door capabilities, the access to flying cars may induce further shifts in individuals' travel behaviour, even in their lifestyle. The fast-growing rate of telecommuting is also expected to alter the patterns and need for travel, especially in the aftermath of COVID-19. Such shifts may entail substantial changes in transportation mode choice, residence location choice, and activity scheduling patterns. With the significant gains in momentum towards the introduction of flying cars, careful exploration of the aforementioned potential impacts of this disruptive technology is warranted in travel demand literature.. In this regard, only a handful of studies investigated the potential impact of emerging transportation technologies on residence relocation choice of individuals. Kim et al. (2020) investigated the impact of autonomous vehicles on residence location and vehicle ownership decisions. Their analysis revealed that individuals who are young, have lower-income level, and individuals who prefer suburban living are more likely to prefer a change on residence location due to the introduction of autonomous vehicles. Moore et al. (2020) investigated the effect of privately owned autonomous vehicles on home and work relocation decisions. Results of this study indicated that individuals who are younger than 35 years old, are tech-savvy, are currently located in suburban area are more likely to consider relocating their home. However, similar conceptual studies investigating the impact of flying cars and urban air mobility on residence location choice are not available in the transportation literature yet.

To that end, this paper seeks to investigate whether the future introduction of flying cars is going to trigger a residence relocation trend among the public, and to identify key factors that are likely to affect the relocation decision. In this regard, an online survey is conducted to obtain

public perceptions and opinions about the operational aspects, and overall impacts of flying cars. Since the concept of flying cars is largely unknown to the public, there is convincing possibility of unobserved heterogeneity affecting the collected opinions. To overcome the challenges associated in subsequent statistical analysis, advanced univariate and bivariate modelling frameworks are implemented to account for the underlying unobserved heterogeneity. Correlated grouped random parameters bivariate probit modelling technique is employed to analyse conceptually similar responses, i.e., public willingness to relocate to areas in close proximity to city centres, and to areas outside dense urban sprawl such as suburban and rural areas. In addition, public willingness not to relocate at all is analysed by estimating a correlated grouped random parameters binary probit model. Both of the aforementioned modelling techniques are capable of accounting for unobserved heterogeneity across observational units, for unbalanced panel effects, for the interaction among unobserved characteristics, and for their effect on the outcome probabilities. The results from the analysis indicate that several socio-demographic characteristics, perceptions and opinions towards flying cars, and behavioural patterns affect public willingness to relocate upon the introduction of flying cars.

2. Data

With an aim to determine individuals' opinions towards the basic characteristics, operational benefits and concerns, and potential usage scenarios of flying cars, a survey was designed with the aid of "SurveyMonkey", an online platform that facilitates conducting online surveys. In March 2017, employees and students from the University at Buffalo distributed the survey among their peers in the United States. A total of 584 responses were collected by 34 distributors. The

responses collected by each individual distributor ranged between 2 and 33. This variation resulted in the formation of groups of observations in the dataset, i.e. unbalanced panels.

In order to make the respondents aware of the characteristics and operation of flying cars, the survey was preceded by a short, yet concise information session consisting of a brief description (as shown in figure A1), several representative images, and a short video of flying cars.

In the first section, the respondents' willingness to adopt flying cars under various ownership and operation scenarios were explored, such as the likelihood of owning and operating, renting, and hiring from ridesharing services. In addition, the individuals' willingness to purchase flying cars under multiple pricing scenarios was also examined.

The next section aimed at collecting opinions towards the anticipated advantages and concerns that may arise with the usage of flying cars in future. Potential advantages included lower and more reliable travel time to destination, reduced traffic congestion on the roadway, along with multiple other cost-, environmental-, and safety-specific advantages that may occur once flying cars are introduced. To capture the respondents' concern-related perceptions, multiple questions focusing on safety-, security-, and operation-related issues were posed in the survey. The latter included the effects of equipment or system failure, accident occurrences on the airway, access to take-off/landing facilities, performance of flying cars in poor weather conditions (e.g., storm, high wind, heavy rain, snow, etc.), and security intrusions by hackers and terrorists, as well as privacy concerns (such as location and destination monitoring) associated with the operation of flying cars. The subsequent section was intended to extract respondents' opinions towards possible measures aiming at enhancing overall security when using flying cars. In addition, the respondents' willingness to use flying cars in multiple trip-specific scenarios was also examined. For example, we investigated the purpose (work, education, entertainment, shopping, and traveling

to the airport), distance (less than 50 miles, 50-100 miles, 100-300 miles, and greater than 300 miles), and temporal distribution of the trip (6:00 AM – 12:00 PM, 12:00PM – 6:00 PM, 6:00 PM – 12:00 AM, and 12:00 AM – 6:00AM).

Given that flying cars are expected to enhance accessibility and mobility, the individuals' willingness to consider relocating their residences was also explored. Specifically, the respondents were asked about the likelihood to consider relocating to the city centre, to an urban area (outside of the city centre), to a suburban area, and to a rural area. Respondents were also asked whether they would consider not relocating at all.

For formulating the questions that aimed to elicit the degree of individuals' concerns, a four-point Likert scale was used. The available options to respond for the concern-related questions were "Not at all concerned", "Slightly concerned", "Moderately concerned", and "Very concerned". The rest of the questions, which focused on the willingness to pay, willingness to use, perceptions towards potential benefits, and the likelihood to consider relocating residences were also formed on a four-point Likert scale, with the available options varying from "very unlikely" or "somewhat unlikely" to "somewhat likely" or "very likely".

Another section of questions aimed to understand respondents' acquaintance of advanced vehicle technologies (e.g., automatic emergency braking (AEB), adaptive cruise control (ACC) system, lane keeping assist system, etc.). These questions are assumed to function as surrogate measures for understanding the respondents' level of familiarity with advanced vehicle technologies or advanced driver assistance systems. The latter may, in turn, affect their perceptual mechanism.

The last section was intended to pick up the respondents' socio-demographic background and behavioural traits. Specifically, the respondents were requested to provide their socio-

demographic characteristics (e.g., age, gender, marital status, level of educational attainment, household income level, and other household characteristics), their driving history (in terms of driving experience, accident involvement counts, and the corresponding accident injury severity level), and their current habitual and behavioural traits (e.g., alcohol consumption, driving habits, self-perceived driving styles, and opinions towards speed limits).

It should be noted that the collected sample consists of individuals, most of whom have a college degree or higher (74.38%, compared to 30.9% in the US). In terms of current residence, the percentage of respondents currently residing in city centres, urban areas (outside of the city centre), suburban areas, and rural areas are 10.39%, 30.39%, 48.83%, and 10.39%, respectively, as presented in Table 1. Additional studies that are conducted based on the survey data discussed above, include the following: Ahmed et al. (2020a, 2021a); Eker et al. (2019, 2020a, 2020b). It should be noted that the present study is part of a series of exploratory studies on public perception towards flying cars. The topics explored in the aforementioned studies include public willingness to use (WTU) and willingness to pay (WTP) for privately owned flying cars, WTU and WTP for shared flying car services, benefits and safety-security related concerns arising from the future use of flying cars. In this study, the goal is to explore whether the mobility benefits likely to be offered by flying cars have the potential to induce residence relocation decision among individuals or not, and identify the factors that are likely to induce such decision.

The responses with respect to respondents' willingness to relocate their residences after the introduction of flying cars are presented in Table 1. The percentage representing the "somewhat or very likely" outcome includes the responses corresponding to "very likely" and "somewhat likely" outcomes. Similarly, the "somewhat or very unlikely" outcome was also aggregated by combining the "very unlikely" and "somewhat unlikely" outcomes. Table 1 shows that 24.22%

and 31.64% of the respondents are willing to relocate to the city centre and to urban areas, respectively. On the contrary, 42.77% and 40.04% of the respondents are willing to relocate to suburban and rural areas, respectively. This indicates that the willingness of the respondents to relocate to suburban and rural areas is more prominent compared to city centre and urban areas. Table 1 also shows that a vast majority of the respondents (73.05%) are inclined towards considering not relocating at all. It should be noted that inconsistent responses were discarded from the statistical analysis. Responses that matched the following criteria were considered as inconsistent: (i) respondents who selected “very unlikely” for either willingness to relocate to the city centre or to urban areas, and willingness to not relocate at all; (ii) respondents who selected “very likely” for either willingness to relocate to the city centre or to urban areas, and willingness to not relocate at all; (iii) respondents who selected “very unlikely” for either willingness to relocate to the suburban or to rural areas, and willingness to not relocate at all; and (iv) respondents who selected “very likely” for either willingness to relocate to the suburban or to rural areas, and willingness to not relocate at all.

The descriptive statistics of key variables that were found to be statistically significant in the statistical analysis are presented in Table 2.

[Insert Table 1 here]

[Insert Table 2 here]

3. Methodology

In order to statistically analyse public willingness to relocate with the future introduction of flying cars, two separate types of discrete data modelling frameworks are adopted in this study: the bivariate probit and the univariate binary probit models.

3.1 The Bivariate Probit Framework

With the future introduction of flying cars, individuals' willingness to relocate their residences to city centre, urban areas, suburban areas, and rural areas might be subjected to systematic unobserved variations. The source of such variations can be traced back to perceptual similarity of locations where the respondents are willing to relocate. For example, the willingness of an individual to relocate to the city centre and the willingness to relocate in an urban area (outside the city centre) might be comprised of similar as well as shared unobserved characteristics. Such shared unobserved characteristics are generally represented by the error terms of the corresponding dependent variables. If two of such dependent variables are taken into consideration, it is highly likely for the error terms to be correlated¹ (Sarwar et al., 2017b). To account for such correlation between the error terms, the bivariate probit modelling framework is employed. With the application of this framework, concurrent modelling of two dependent variables that are binary, and share similar unobserved variations is possible while simultaneously accounting for the cross-equation error term correlation.

To conduct an in-depth statistical analysis of public willingness to relocate, the bivariate probit modelling framework is employed. The selection of this framework is warranted since the ordinal responses from the survey were consolidated to form two discrete outcomes. Specifically,

¹ It should be noted that the pairs of dependent variables for the bivariate probit model were selected based on correlation matrix retrieved from a multivariate probit model. Pairs with higher correlation coefficient were selected over others. This correlation matrix is presented in table A2.

the first four dependent variables representing willingness to relocate have two discrete outcomes as follows: “somewhat or very likely” and “somewhat or very unlikely”. The bivariate probit model can be defined as (Sanko et al., 2014; Greene, 2017; Sarwar et al., 2017a; Eker et al., 2019; Fountas et al., 2019; Ahmed et al., 2020b):

$$\begin{aligned} V_{i,1} &= \boldsymbol{\beta}_{i,1} \mathbf{X}_{i,1} + \varepsilon_{i,1}, & v_{i,1} &= 1 \text{ if } V_{i,1} > 0, \text{ and } v_{i,1} = 0 \text{ otherwise} \\ V_{i,2} &= \boldsymbol{\beta}_{i,2} \mathbf{X}_{i,2} + \varepsilon_{i,2}, & v_{i,2} &= 1 \text{ if } V_{i,2} > 0, \text{ and } v_{i,2} = 0 \text{ otherwise} \end{aligned} \quad (1)$$

where the error terms are expressed as:

$$\begin{pmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right] \quad (2)$$

Here, \mathbf{X} is a vector of explanatory variables that affect willingness to relocate of an individual i , $\boldsymbol{\beta}$ is a vector of estimable parameters with respect to \mathbf{X} , $v_{i,1}$ and $v_{i,2}$ correspond to integer binary outcomes of the dependent variables, $V_{i,1}$ and $V_{i,2}$ are latent variables, ε is a random error term (assumed to follow the standard normal distribution, with mean equal to zero and variance equal to one), and ρ is the cross-equation correlation coefficient of the error terms. The bivariate normal density function and the corresponding log-likelihood function are then respectively formulated as (Greene, 2017),

$$\phi(V_1, V_2, \rho) = \frac{\exp \left[-0.5(V_1^2 + V_2^2 - 2\rho V_1 V_2) / (1 - \rho^2) \right]}{\left[2\pi \sqrt{(1 - \rho^2)} \right]} \quad (3)$$

and

$$\begin{aligned} LL = \sum_{i=1}^N & [v_{i,1} v_{i,2} \ln \Phi(\boldsymbol{\beta}_{i,1} \mathbf{X}_{i,1}, \boldsymbol{\beta}_{i,2} \mathbf{X}_{i,2}, \rho) + (1 - v_{i,1}) v_{i,2} \ln \Phi(-\boldsymbol{\beta}_{i,1} \mathbf{X}_{i,1}, \boldsymbol{\beta}_{i,2} \mathbf{X}_{i,2}, -\rho) \\ & + (1 - v_{i,2}) v_{i,1} \ln \Phi(\boldsymbol{\beta}_{i,1} \mathbf{X}_{i,1}, -\boldsymbol{\beta}_{i,2} \mathbf{X}_{i,2}, -\rho) + (1 - v_{i,1})(1 - v_{i,2}) \ln \Phi(-\boldsymbol{\beta}_{i,1} \mathbf{X}_{i,1}, -\boldsymbol{\beta}_{i,2} \mathbf{X}_{i,2}, \rho)] \end{aligned} \quad (4)$$

3.2 The univariate binary probit framework

The dependent variable representing the likelihood of individuals not relocating at all with the introduction of flying cars is also specified to have two aggregate outcomes: “somewhat or very likely” and “somewhat or very unlikely”. Thus, the variable is binary in nature. In order to statistically analyse the latter, the univariate binary probit modelling framework is employed. The binary probit model is defined as (Greene, 2017),

$$Z_i = \beta_1 \mathbf{X}_i + \varepsilon_i, \quad z_i = 1 \text{ if } Z_i > 0, \text{ and } z_i = 0 \text{ otherwise} \quad (5)$$

where, \mathbf{X} is a vector of explanatory variables that determines the individuals’ likelihood of not relocating at all, β is a vector of estimable parameters corresponding to \mathbf{X} , z is the observed binary outcome (one or zero), Z_i is a latent variable, and ε denotes a random disturbance term assumed to follow the standard normal distribution.

3.3 Addressing unobserved heterogeneity: correlated grouped random parameters approach

In a survey-based data collection procedure, it is often quite challenging to capture the respondents’ personal preferences and priorities, behavioural, attitudinal, and commuting patterns, or their restricted exposure to new technologies. The absence of such information introduces additional sources of underlying systematic variations, i.e., unobserved heterogeneity. To account for the effects of unobserved heterogeneity on the statistical modelling of survey data (Mannering and Bhat, 2014; Mannering et al., 2016; Fountas and Anastasopoulos, 2017; Anowar and Eluru, 2018; Sarwar et al., 2018; Chen et al., 2019), random parameters are introduced into both the bivariate probit and univariate binary probit modelling frameworks. In the random parameters modelling approach, the model parameters are allowed to vary across the observational units (individual observation, spatial unit, or group of observations). In this paper, each survey response constitutes the most basic observational unit. However, it is likely that the responses collected by

the same survey distributor may share similar, systematic unobserved variations, resulting in unbalanced panel effects in the dataset. To account for such panel effects, grouped random parameters are introduced. The latter allow the estimable parameters to vary across groups of distributor-specific responses. Grouped random parameters are defined as (Dong et al., 2016; Murillo-Hoyos et al., 2016; Sarwar et al., 2017a; Fountas et al., 2018a; Fountas et al., 2018b; Fountas et al., 2019; Pantangi et al., 2019; Pantangi et al., 2020; Intini et al., 2020; Pantangi et al., 2021; Ahmed et al., 2021b):

$$\boldsymbol{\beta}_j = \boldsymbol{\beta} + \Gamma \omega_j \quad (6)$$

where, $\boldsymbol{\beta}$ denotes the mean of the random parameter vector, Γ is a symmetric matrix (also known as Cholesky matrix (Greene, 2017)), and ω_j is a randomly distributed, distributor-specific term, which can take form of any of the several commonly used distributions (e.g., normal, log-normal, triangular, uniform, and Weibull), and the subscript j denotes individual distributors in the data. In this study, it was found that among all the available distributional forms, normal distribution provided the best statistical fit. Hence, the latter was employed in the model estimation process, and the resulting mean and standard deviation for ω_j were zero and σ^2 , respectively.

To account for the possible correlation between the random parameters, an unrestrictive form of the Cholesky matrix is implemented where the non-diagonal elements are allowed to take non-zero values (contrary to the uncorrelated random parameters approach, where the non-diagonal elements are restricted to zero). The latter are capable of indirectly capturing the correlation effects between the unobserved characteristics captured by the random parameters. The correlation coefficients add to the explanatory power of the modelling framework by indicating unobserved heterogeneity interactions as well as their effect on the outcome probabilities.

The diagonal and off-diagonal elements of the Γ matrix are used to compute the standard deviation of each of the correlated grouped random parameters, as follows:

$$\mu_j = \sqrt{\mu_{k,k}^2 + \mu_{k,k-1}^2 + \mu_{k,k-2}^2 + \dots + \mu_{k,1}^2} \quad (7)$$

where μ_j indicates the standard deviation of the random parameter, $\mu_{k,k}$ are the corresponding diagonal elements, and $\mu_{k,k-1}, \mu_{k,k-2} \dots \mu_{k,1}$ are the off-diagonal non-zero elements of the estimated Cholesky matrix. The computation of standard error, and t -statistics of the standard deviations is conducted by implementing the methodology outlined in (Fountas et al., 2018b):

$$SE_{\mu_j} = \frac{S_{\mu_{jn}}}{\sqrt{N}} \quad (8)$$

where, SE_{μ_j} is the standard error of the standard deviation (averaged across the observational units), $S_{\mu_{jn}}$ is the standard deviation of the observational unit specific μ_{jn} , and N is the number of panels in this specific case. The corresponding t -statistic is then computed as,

$$t_{\mu_j} = \frac{\mu_j}{SE_{\mu_j}} \quad (9)$$

A simulated maximum likelihood approach was implemented for the model estimation process. The computationally demanding numerical integration process was streamlined by employing Halton draws (Halton, 1960). Note that utilizing 600 Halton draws provided stable parameter estimates in this study (Mannering and Bhat, 2014; Sarwar et al., 2017a; Fountas et al., 2019; Pantangi et al., 2019).

To understand the magnitude of the effects of the independent variables on individuals' likelihood to relocate, elasticities and pseudo-elasticities are computed. The elasticities measure

the effect of 1% change in any continuous independent variable on the probability outcome of the dependent variable. It is defined as (Greene, 2016),

$$E = \frac{\partial F(\boldsymbol{\beta}'\mathbf{x})}{\partial x_i} = f(\boldsymbol{\beta}'\mathbf{x})\beta_i \quad (10)$$

where, $f(\boldsymbol{\beta}'\mathbf{x})$ is the probit density function, and β_i is the estimated coefficient of the explanatory continuous variable x_i , for which the elasticity is computed. Since the majority of the independent variables used in this study are indicator variables, the effect of an independent variable changing from “0” to “1” on the outcome probability of the dependent variable is computed as (Greene, 2016),

$$E = F(\boldsymbol{\beta}'\mathbf{x} + \alpha_i) - F(\boldsymbol{\beta}'\mathbf{x}) \quad (11)$$

where, \mathbf{x} and $\boldsymbol{\beta}$ are vectors of explanatory variables and corresponding estimated coefficients (excluding the explanatory indicator variable x_i and the corresponding estimated coefficient), respectively; and α_i is the estimated coefficient for the indicator variable x_i , for which the elasticity is computed. It should be noted that Equations 10 and 11 are applicable for the univariate probit modelling framework. To compute elasticity and pseudo-elasticity in the bivariate probit framework, the procedure outlined by Greene (2016; 2017) was utilized.

4. Model estimation results

For the first two pairs of dependent variables derived from the survey responses, correlated grouped random parameters bivariate probit models were estimated. The pair selection mechanism of the dependent variables under consideration followed two criteria: the conceptual proximity of the survey responses; and, the identification of statistically significant error-term correlation between the dependent variables derived from the proximal survey responses. Furthermore, in order to investigate individuals' unwillingness to relocate, a correlated grouped random parameters binary probit model was estimated.

Note that all possible combinations of the available independent variables were evaluated in the model estimation process. The final model specifications only included variables that were found to be statistically significant at a significance level of $\alpha = 0.10$. Regarding the random parameters, the statistical significance of the means and standard deviations were evaluated using the same criterion. However, if a random parameter's standard deviation was found to be statistically significant, but the mean was statistically insignificant, a likelihood ratio test (chi-square distributed) with degree of freedom equal to two (representing the mean and the standard deviation of the random parameter under consideration) was performed to determine the overall gain in the statistical fit of the model (Washington et al., 2020; Greene, 2017). If the overall gain in model fit was found to be statistically significant (at a 0.90 level of confidence or greater), only then the random parameter was included in the model specification.

4.1 Willingness to consider relocating to city centre and urban area (outside the city centre)

The estimation results and (pseudo-)elasticities of the bivariate probit model of individuals' willingness to consider relocating to city centre and urban areas (outside the city centre) are

presented in Table 3 and Table 6, respectively. Table 4 presents the aggregate distributional effect of the random parameter density functions. Since all random parameters were specified to be normally distributed, the above zero percentages presented in table 4 indicates the area under the normal distribution curve belonging to the positive portion, and *vice versa*. It should be noted that the magnitude and statistical significance of the cross-equation error correlation term for the aforementioned model support the use of the bivariate probit modelling framework.

[Insert Table 3 here]

The results reveal that a number of socio-demographic characteristics affect the individuals' willingness to relocate to urban areas after the introduction of flying cars. The variable representing the age of the respondents had a negative effect (by -0.008 and -0.006, respectively; as indicated by the elasticity in Table 6) on the willingness of the respondents to relocate to the city centre and an urban area (outside the city centre). Older individuals, despite gaining access to emerging technologies, tend to be less open towards embracing changes in their lifestyle patterns. Such behavioural tendency can be attributed to their lack of exposure to emerging transportation technologies, or to their bias against operational reliability of the latter (Eker et al., 2019). Similarly, Caucasian respondents were less likely (by -0.085 and -0.117, as indicated by the pseudo-elasticity in Table 6) to consider relocating to city centre and urban areas. Furthermore, individuals currently living in suburban or rural areas demonstrated a negative attitude (by -0.130 and -0.113, as indicated by the pseudo-elasticities in Table 6) towards considering relocating to city centres and urban areas. Previous studies have shown that the choice of residing in suburban areas is driven by the amenities offered by suburban living, as for example, larger residence, and

presence of driveways in conjunction with the freedom of movement offered by driving privately owned vehicles (Bagley and Mokhtarian, 2002; Næss et al., 2018). The travel time benefits likely to be offered by flying cars further enhances the preference towards suburban living, while reaping the added advantage of lower travel time likely to be offered by flying cars.

Moving to the respondents' familiarity with advanced vehicle safety features, individuals who are familiar with left-turn assist feature were more likely (by 0.089 and 0.110, as indicated by the pseudo-elasticity in Table 6) to consider relocating to city centres and urban areas. This finding shows that tech-savvy individuals, who are anticipated to be among the earliest consumers of flying cars (Eker et al., 2019), are willing to reduce the time spent in traveling by moving to city centre and urban areas, which in turn may contribute to an increased participation in professional, social and entertainment-related activities.

As far as the perceptual opinions towards flying cars are concerned, individuals who are expecting a reduction in vehicle maintenance cost were more likely (by 0.138, as indicated by the pseudo-elasticity in Table 6) to consider relocating to city centres. The possibility of lower transportation-related expenses in conjunction with the broader access to flexible mobility offered by flying cars may provide such individuals with lucrative incentives to consider relocating to city centres. Individuals who are willing to use flying cars for airport access trips were more likely (by 0.107 and 0.151, respectively, as indicated by the pseudo-elasticities in Table 6) to consider relocating to city centre and urban areas (outside the city centre). This is a particularly interesting finding. In recent years, the distances of newly constructed airports from the central business districts of the cities they serve have been steadily increasing, ranging between 20 to 45 miles and beyond (Rodrigue et al., 2016). With the use of flying cars, the anticipated reduction and increased reliability of travel time to such airports located at significant distance from city centres might be

the underlying determinant in this case. In addition, individuals may perceive the airport infrastructure as the most appropriate setting for ensuring safe and smooth flying car operations.

Finally, individuals who endorse the implementation of existing FAA regulations for air traffic control have mixed opinion towards the likelihood of relocating to urban area (outside the city centre). Specifically, 65.29% of these respondents were likely to relocate to urban areas with the future introduction of flying cars, whereas the opposite was observed for the remaining 34.71% of the respondents.

[Insert Table 4 here]

4.2 Willingness to consider relocating to suburban and rural area

The model estimation results and (pseudo-)elasticities of the bivariate probit model of individuals' willingness to consider relocating to suburban and rural area with the future introduction of flying cars are presented in Table 3 and Table 6, respectively. In line with the first bivariate probit model, the magnitude and statistical significance of the cross-equation error correlation term for this model justifies the use of the bivariate probit modelling framework.

Several socio-demographic characteristics were observed to affect the individuals' willingness to relocate to suburban and rural areas. In line with the findings from the previous model, older individuals were less likely (by -0.005 and -0.002, respectively, as indicated by the pseudo-elasticities in Table 6) to consider relocating to suburban and rural area. Asian respondents were more likely (by 0.062, as indicated by the pseudo-elasticity in Table 6) to consider relocating to suburban areas.

Turning to the perceptual opinions towards flying cars, respondents who are expecting a reduction in CO₂ emission with the introduction of flying cars were more likely to relocate to rural

areas (by 0.143, as indicated by the pseudo-elasticity in Table 6). The majority (76.48%, as indicated in Table 4) of the respondents from the same group were willing to relocate to suburban areas. The opposite effect was observed for the remaining 23.52% of the respondents. One of the anticipated effects of relocating to suburban and rural areas would be an overall increase in travel distances. CO₂ emission from the use of existing transportation mode for such longer trips would be counterbalanced by reduced CO₂ emission from the use of flying cars in exact same trip scenarios. Individuals who are willing to use flying cars for 50-100 miles long trips were more likely (by 0.094 and 0.230, respectively, as shown by the pseudo-elasticities in Table 6) to consider relocating to suburban and rural areas. Intuitively, the likelihood of flying cars offering reduced and more reliable travel times would incentivize the potential users to relocate further away from their frequent destinations e.g., workplace, educational institution, entertainment, and so on.

Focusing on the opinions towards potential security measures, respondents who endorse the establishment of air-road police with flying patrol cars to improve security against hackers and terrorists were more likely (by 0.047, as shown by the pseudo-elasticity presented in Table 6) to consider relocating to suburban areas. However, respondents who favour the implementation of existing FAA regulations for air traffic control had mixed opinion towards a possible relocation to rural areas. Specifically, 80.90% of the latter respondents were more likely to consider relocating to a rural area, whereas the opposite was observed for the remaining 19.10% (as indicated in Table 4).

4.3 Unwillingness to consider relocating

The estimation results and (pseudo-)elasticities of the correlated grouped random parameters binary probit model of public willingness to consider not relocating at all are presented in Table 3 and Table 6, respectively.

In line with the observations from the previously discussed models, older individuals were more likely (by 0.004, as indicated by the pseudo-elasticity in Table 6) to consider not relocating at all. This observation is in agreement with the finding by Kim et al. (2020), where residence relocation potential was investigated given that autonomous vehicles are introduced. However, individuals who grew up in urban areas were less likely (by -0.138, as shown by pseudo-elasticities presented in Table 6) to consider not relocating. Growing up in dense urban environment may foster a more exploratory behaviour for some individuals. The forthcoming introduction of flying cars in the existing traffic network may stimulate such individuals to explore new residence locations, providing that the mobility benefits offered by flying cars are going to be utilized to the fullest.

[Insert Table 5 here]

Focusing on familiarity with advanced vehicle safety features, it is observed that individuals' who are familiar with the adaptive cruise control were more likely to consider not relocating. In this context, it should be noted that recent studies have shown the positive effect of respondents' familiarity with advanced vehicle safety features on the willingness to use and pay for flying cars (Al Haddad et al., 2020; Eker et al., 2020b). While the aforementioned observation is not in direct contrast with the findings from other studies in the literature, it indicates the

necessity to further investigate this issue (by conducting additional surveys) and evaluate whether this finding remains stable across time. In addition, individuals who are expecting more in-vehicle activities (e.g., work, productivity or entertainment), were also more likely to consider not relocating. Previous research has demonstrated the negative effect of in-vehicle activities on overall travel satisfaction of the passengers (Ettema et al., 2012). On a similar note, this finding shows that the possible increase of in-vehicle activities with the use of flying cars may discourage potential users to explore new residence locations, which in turn, might contribute to a decrease in overall travel satisfaction. Individuals who support the use of existing FAA regulations for air traffic control had mixed opinion towards considering not relocating. About 62% of the respondents from this group were not willing to relocate, whereas the opposite was observed for the remaining 38% (as indicated in Table 4).

Turning to the behavioural traits, individuals who identify themselves as non-aggressive drivers were associated with mixed willingness to relocate. About 33% of the respondents from this group were not willing to relocate; whereas the opposite was observed for the remaining 67% (as indicated in Table 4). In addition, individuals who disagree with the suggestive role of speed limits in highways were less likely (by -0.167, as shown by the pseudo-elasticity in Table 6) to consider not relocating with the introduction of flying cars. Previous study has shown that the self-identified, non-aggressive driving behaviour contributes in forming a more welcoming attitude towards the use of flying cars (Eker et al., 2019). Following the similar perceptual path, the same group of individuals are more willing to reconsider their residential choice by leveraging the anticipated mobility benefits offered by flying cars.

[Insert Table 6 here]

4.4 Interpretation of random parameters correlation

The correlation coefficients of random parameters, as presented in Table 5, provide further insights into the interactions among the unobserved factors captured by the random parameters and their effect on public willingness to relocate. In the model for the willingness to relocate to suburban and rural areas, the environmental benefit indicator (representing expectation of less CO₂ emissions) and security measure indicator (reflecting endorsement of existing FAA regulations for air traffic control) resulted in positively correlated (the coefficient is 0.399, as shown in Table 5) grouped random parameters. The latter indicates that the combination of the unobserved characteristics has a homogeneous effect on public willingness to consider relocating to suburban and rural areas. Moving to the model of considering not relocating at all, the same security measure indicator as in the previous model and the aggressive driving indicator (reflecting self-identified non-aggressive drivers) produced negatively correlated (the coefficient is -0.703, as shown in Table 5) grouped random parameters, thus implying a heterogeneous effect on willingness to consider not relocating at all. It should be noted that correlation between random parameters was not found in the model for willingness to relocate to city centres and urban areas.

5. Policy implications

The findings from this study can be used to delineate a preliminary policy framework based on scenario-specific outcomes, which would aid transportation engineers and urban planners to envision the future of cities, and of suburban and rural areas. Identifying the socio-demographic characteristics of individuals that are willing to relocate with the future introduction of flying cars have the potential to play a significant role in developing land-use and urban planning policies. Such policies may aid ensuring smooth transition to the emerging transportation systems, and sustainable management of the existing and newly added travel demand. In addition, despite the

willingness of some individuals to use flying cars for various trip purposes, there exist concerns related to security issues arising from the operation of flying cars. With respect to residence relocation, devising necessary preventive security measures while taking the findings from this study into account would play significant role in preparing localities to utilize flying cars for door-to-door transportation. The use of flying cars to access facilities such as airports, would also have impacts on the provision and usage of parking, pick-up and drop-off spaces. Furthermore, transportation infrastructures, e.g., roadways, transportation hubs, transit stations, bus stations, recharging and refuelling spots would also be affected by the introduction and use of flying cars. The need for new infrastructure (e.g., vertiports, air taxi hubs) is also expected to further inform the existing principles of land use planning and urban form development. The findings indicating willingness to use coupled with corresponding socio-demographic characteristics can be taken into account by the authorities and planners to begin transforming design and conceptual models of spatial planning to accommodate the operation of flying cars. Finally, the socio-demographic and behavioural characteristics of individuals identified in this study can help public agencies, flying car manufacturers, and mobility service providers, to cooperate and devise strategies to aid seamless transition towards flying car usage and corresponding residence relocation for the targeted groups.

6. Discussion and conclusions

The swift technological advancements in conjunction with the ever-rising demand for innovative and efficient transportation services has led to the development of a new transportation mode, namely the flying car. Despite the forthcoming introduction of the latter, the potential impacts of this technology on the travel behaviour and lifestyle choices of the general public have not been explored yet. The capability of flying cars to offer lower and more reliable travel times coupled

with door-to-door mobility services may lead to major transformations in travel behaviour patterns and the very fabric of urban form as we know it to date. In this context, this paper seeks to identify various determinants of public willingness to consider residence relocation after the emergence of flying cars. For this purpose, public opinions, perceptions and preferences regarding flying cars, as well as socio-demographic characteristics of 584 respondents from the United States were collected by conducting an online survey. It should be noted that 74.38% of the respondents have a college degree or higher, as compared to 30.9% on a national level in the US.

Since public exposure to the concept of flying cars was limited at the time of the survey, the collected opinions, perceptions and preferences may exhibit complex unobserved heterogeneity patterns. To account for the possibility of commonly shared unobserved characteristics affecting conceptually similar opinions, the bivariate modelling framework was employed. Furthermore, the possibility of unobserved characteristics systematically varying across groups of observations, and the interaction among them were accounted for by employing correlated grouped random parameters in the model estimation. Therefore, correlated grouped random parameters bivariate probit models were estimated to identify the key factors that may affect the individuals' willingness to relocate. In addition, to identify the determinants of public willingness to consider not relocating at all, a correlated grouped random parameters binary probit model was estimated. Use of the aforementioned statistical modelling frameworks are also - to a significant extent - accounting for the issue of the highly educated respondents in the sample. In this context, a relaxed significance level threshold of 0.1 was used in this study to identify statistically significant variables.

The statistical analysis revealed that multiple socio-demographic and behavioural characteristics, and perceptual patterns towards flying cars affect respondents' willingness to

consider relocating their residence. Older individuals were found to be more reluctant to consider relocating their residences, despite the significant mobility benefits likely to be offered by flying cars. Individuals currently living in suburban or rural areas were less likely to consider relocating to city centres and urban areas due to the amenities offered by suburban living. Eco-conscious individuals (who expect reduction in emissions from flying car usage) were more likely to consider relocating to rural areas, whereas the same group of individuals had mixed opinions towards the option of relocating to suburban areas. Willingness to use flying cars for traveling to the airport was found to influence respondents' preferences for relocating their households to city centres or urban areas. Respondents expressing preference to relocate to city centres would gain high accessibility to airports that are located farther away from city centres through the use of flying cars. This is intuitive in the context of the United States, where the majority of the airports are located farther away from the city centres. However, in the context of other countries (e.g., most European countries) where the majority of the airports are located close to city centres, further investigation is warranted. Use of flying cars for small-to-medium distance trips for various purposes (work, education, entertainment etc.) was found to induce inclination towards relocating to suburban and rural areas. Interestingly, perceptions towards mobility benefits of flying cars on travel times, congestion, and road safety were not found to affect respondents' residence relocation intents, which warrants further investigation. This finding is in contrast to prior studies that focused on transportation and land use feedback cycle, where accessibility to transportation modes and infrastructures were found to play significant role in relocation decisions (Glen et al., 1980; Kwan and Weber, 2008).

The mobility benefits that will possibly emerge from the introduction of flying cars have the potential to transform travel behaviour to a significant extent. Such transformations may lead

to the re-evaluation of priorities in regional and urban planning, due to possible shifts in housing policy and household locations. The expected interrelationship between urban air mobility and residential mobility may also pose new challenges to the transportation planning process, as the trip generation and distribution patterns may change spatially and temporally (Anastasopoulos et al., 2010; Mannering, 2018; Tischer et al., 2019). Hence, the outcomes of this study can assist transportation planners, urban and regional planning authorities, and transportation service providers to initiate necessary actions to assess the impacts of flying cars on travel demand at an interregional level. However, the nature of the collected sample is a limitation of this study, and further investigation is warranted to validate the findings presented herein.

It is important to note that in addition to autonomous vehicles, flying car is an emergent form of transportation technology, and the notion of flying car as a transportation mode is becoming more widespread through online news outlets and regular press releases from large manufacturers and Public Authorities. This is resulting in greater public exposure of flying cars to the general population, which in turn, is likely to cause shifts in public perception as well. To track the direction of such changes, future research should focus on continuous evaluation of public perception by acquiring larger and more representative samples of the general population. In addition, potential impacts of autonomous vehicles, flying cars and advanced air mobility services on urban and rural transportation, as well as on long term residence location choice of individuals should be investigated. Furthermore, future research can simultaneously explore the potential changes in urban, suburban and rural landscapes, in terms of land use and urban planning, from the introduction of the aforementioned emerging transportation technologies.

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Table 1. Distribution of respondents' willingness to relocate with the introduction of flying cars, and location of their current residence

Dependent Variables	Very unlikely	Somewhat unlikely	Somewhat or very unlikely	Somewhat likely	Very likely	Somewhat or very likely
With the introduction of flying cars, how likely is it for you to consider:						
Relocating to the city centre?	47.27%	28.52%	75.78%	20.12%	4.10%	24.22%
Relocating to an urban area (but outside the city centre)?	39.45%	28.91%	68.36%	27.34%	4.30%	31.64%
Relocating to a suburban area?	34.77%	22.46%	57.23%	34.38%	8.40%	42.77%
Relocating to a rural area?	35.55%	24.41%	59.96%	28.91%	11.13%	40.04%
Not relocating at all?	13.09%	13.87%	26.95%	26.76%	46.29%	73.05%
Current residence of the respondents	Percentage					
City centre	10.39%					
Urban area (outside the city centre)	30.39%					
Suburban area	48.83%					
Rural area	10.39%					

Table 2. Descriptive statistics of the statistically significant variables (N=584)

Variable Description	Mean	Std. Dev.	Min.	Max.
Socio-demographic Characteristics				
Age of the respondent	29.896	12.760	16	94
Current neighbourhood indicator (1 if the respondent is currently living suburban or rural area, 0 otherwise)	0.533	0.499	0	1
Ethnicity indicator (1 if the respondent is Caucasian, 0 otherwise)	0.559	0.497	0	1
Ethnicity indicator (1 if the respondent is Asian, 0 otherwise)	0.169	0.375	0	1
Childhood living area indicator (1 if the respondent grew up in urban area, 0 otherwise)	0.208	0.406	0	1
Opinions and Preferences				
Vehicle safety features indicator (1 if the respondent is familiar with adaptive cruise control feature, 0 otherwise)	0.702	0.458	0	1
Vehicle safety features indicator (1 if the respondent is familiar with left turn assist feature, 0 otherwise)	0.423	0.495	0	1
Cost benefit indicator (1 if the respondent thinks that lower vehicle maintenance cost is likely to occur with the introduction of flying cars, 0 otherwise)	0.238	0.426	0	1
Environmental benefit indicator (1 if the respondent thinks that less CO ₂ emission is likely with the introduction of flying cars, 0 otherwise)	0.296	0.457	0	1
In-vehicle activity indicator (1 if the respondent thinks more in-vehicle non-driving activities are likely, 0 otherwise)	0.631	0.483	0	1
Willingness to use indicator (1 if the respondent is willing to use flying cars for 50-100 mile long trips, 0 otherwise)	0.534	0.499	0	1
Willingness to use indicator (1 if the respondent is willing to use flying cars for airport access trips, 0 otherwise)	0.422	0.494	0	1
Security measure indicator (1 if the respondent thinks that using existing FAA regulations for air traffic control is very likely to improve security against hackers/terrorists, 0 otherwise)	0.169	0.375	0	1
Security measure indicator (1 if the respondent thinks that using existing FAA regulations for air traffic control is likely to improve security against hackers/terrorists, 0 otherwise)	0.550	0.498	0	1
Security measure indicator (1 if the respondent thinks that establishing air-road police enforcement – with flying police cars – is likely to improve security against hackers/terrorists, 0 otherwise)	0.637	0.481	0	1
Speed limit opinion indicator (1 if the respondent disagrees with the statement: “Speed limits on high speed freeways should only be suggestive”, 0 otherwise)	0.182	0.386	0	1
Aggressive driving indicator (1 if the respondent thinks that s/he normally drives not aggressively, 0 otherwise)	0.374	0.484	0	1

Table 3. Estimation results of the correlated grouped random parameters bivariate probit models and binary probit model of individuals' willingness to relocate with the future introduction of flying cars (N=584)

Variable	Bivariate probit		Bivariate probit		Binary probit
	Likelihood of relocating to city centre	Likelihood of relocating to urban area (outside the city centre)	Likelihood of relocating to suburban area	Likelihood of relocating to rural area	Likelihood of not relocating at all
	Coeff. (t-stat)	Coeff. (t-stat)	Coeff. (t-stat)	Coeff. (t-stat)	Coeff. (t-stat)
Constant	—	—	—	-0.484 (-2.38)	—
Socio-demographic characteristics					
Age of the respondent	-0.025 (-4.92)	-0.017 (-2.71)	-0.029 (-8.59)	-0.013 (-2.43)	0.011 (2.53)
Current neighbourhood indicator (1 if the respondent is currently living in suburban or rural area, 0 otherwise)	-0.520 (-3.22)	-0.365 (-2.09)	—	—	—
Ethnicity indicator (1 if the respondent is Caucasian, 0 otherwise)	-0.368 (-2.24)	-0.406 (-3.03)	—	—	—
Ethnicity indicator (1 if the respondent is Asian, 0 otherwise)	—	—	0.417 (3.73)	—	—
Childhood living area indicator (1 if the respondent grew up in urban area, 0 otherwise)	—	—	—	—	-0.372 (-1.83)
Opinions and Preferences					
Vehicle safety features indicator (1 if the respondent is familiar with adaptive cruise control feature, 0 otherwise)	—	—	—	—	0.411 (2.75)
Vehicle safety features indicator (1 if the respondent is familiar with left turn assist feature, 0 otherwise)	0.332 (2.27)	0.342 (2.47)	—	—	—
Cost benefit indicator (1 if the respondent thinks that lower vehicle maintenance cost is likely to occur with the introduction of flying cars, 0 otherwise)	0.415 (3.11)	—	—	—	—
Environmental benefit indicator (1 if the respondent thinks that less CO ₂ emission is likely with the introduction of flying cars, 0 otherwise)	—	—	0.358 (2.15)	0.308 (1.96)	—
<i>Standard deviation of parameter distribution</i>	—	—	0.496 (3.90)	—	—
In-vehicle activity indicator (1 if the respondent thinks more in-vehicle non-driving activities are likely with the introduction of flying cars, 0 otherwise)	—	—	—	—	0.409 (2.51)
Willingness to use indicator (1 if the respondent is willing to use flying cars for 50-100 mile long trips, 0 otherwise)	—	—	0.470 (4.05)	0.516 (4.29)	—
Willingness to use indicator (1 if the respondent is willing to use flying cars for airport access trips, 0 otherwise)	0.396 (2.59)	0.477 (3.72)	—	—	—

Variable	Bivariate probit		Bivariate probit		Binary probit
	Likelihood of relocating to city centre	Likelihood of relocating to urban area (outside the city centre)	Likelihood of relocating to suburban area	Likelihood of relocating to rural area	Likelihood of not relocating at all
	Coeff. (t-stat)	Coeff. (t-stat)	Coeff. (t-stat)	Coeff. (t-stat)	Coeff. (t-stat)
Security measure indicator (1 if the respondent thinks that using existing FAA regulations for air traffic control is very likely to improve security against hackers/terrorists, 0 otherwise)	—	0.272 (1.56)	—	—	—
<i>Standard deviation of parameter distribution</i>	—	0.692 (3.71)	—	—	—
Security measure indicator (1 if the respondent thinks that using existing FAA regulations for air traffic control is likely to improve security against hackers/terrorists, 0 otherwise)	—	—	—	0.334 (2.46)	0.126 (0.87)
<i>Standard deviation of parameter distribution</i>	—	—	—	0.382 (20.60)	0.421 (3.97)
Security measure indicator (1 if the respondent thinks that establishing air-road police enforcement – with flying police cars – is likely to improve security against hackers/terrorists, 0 otherwise)	—	—	0.313 (2.77)	—	—
Speed limit opinion indicator (1 if the respondent disagrees with the statement: “Speed limits on high speed freeways should only be suggestive”, 0 otherwise)	—	—	—	—	-0.390 (-2.10)
Aggressive driving indicator (1 if the respondent thinks that s/he normally drives non-aggressively, 0 otherwise)	—	—	—	—	-0.273 (-1.76)
<i>Standard deviation of parameter distribution</i>	—	—	—	—	0.618 (23.21)
Cross equation correlation (t-stat)	0.779 (14.51)		0.713 (14.17)		—
Number of survey distributors	34		34		34
Number of respondents	486		514		516
Number of estimated parameters	14		14		10
Log-likelihood at convergence	-428.224		-542.749		-256.552
Log-likelihood at zero	-562.274		-697.021		-300.643
McFadden pseudo- ρ square	0.238		0.221		0.147
McFadden corrected pseudo- ρ square	0.214		0.201		0.113
Akaike information criterion (AIC)	884.4		1113.5		533.1

“—”: Variables that were not included in the corresponding model.

Table 4. Aggregate distributional effect of the random parameter density functions across respondents (N=584)

Likelihood of relocating to city center and urban areas (outside city center)		
	Above zero	Below zero
Security measure indicator (1 if the respondent thinks that using existing FAA regulations for air traffic control is very likely to improve security against hackers/terrorists, 0 otherwise)	65.29%	34.71%
Likelihood of relocating to suburban and rural areas		
	Above zero	Below zero
Environmental benefit indicator (1 if the respondent thinks that less CO ₂ emission is likely with the introduction of flying cars, 0 otherwise)	76.48%	23.52%
Security measure indicator (1 if the respondent thinks that using existing FAA regulations for air traffic control is likely to improve security against hackers/terrorists, 0 otherwise)	80.90%	19.10%
Likelihood of not relocating at all		
	Above zero	Below zero
Security measure indicator (1 if the respondent thinks that using existing FAA regulations for air traffic control is likely to improve security against hackers/terrorists, 0 otherwise)	61.76%	38.24%
Aggressive driving indicator (1 if the respondent thinks that s/he normally drives not aggressively, 0 otherwise)	32.93%	67.07%

Table 5. Elements of the Cholesky matrix (*t*-stats on parentheses), and correlation coefficients of the random parameters (in brackets) (N=584)

Likelihood of relocating to suburban and rural areas		
	Environmental benefit indicator (1 if the respondent thinks that less CO2 emission is likely with the introduction of flying cars, 0 otherwise)	Security measure indicator (1 if the respondent thinks that using existing FAA regulations for air traffic control is likely to improve security against hackers/terrorists, 0 otherwise)
Environmental benefit indicator (1 if the respondent thinks that less CO2 emission is likely with the introduction of flying cars, 0 otherwise)	0.495 (3.90) [1.000]	0.152 (2.05) [0.399]
Security measure indicator (1 if the respondent thinks that using existing FAA regulations for air traffic control is likely to improve security against hackers/terrorists, 0 otherwise)	0.152 (2.05) [0.399]	0.350 (4.43) [1.000]
Likelihood of not relocating at all		
	Security measure indicator (1 if the respondent thinks that using existing FAA regulations for air traffic control is likely to improve security against hackers/terrorists, 0 otherwise)	Aggressive driving indicator (1 if the respondent thinks that s/he normally drives not aggressively, 0 otherwise)
Security measure indicator (1 if the respondent thinks that using existing FAA regulations for air traffic control is likely to improve security against hackers/terrorists, 0 otherwise)	0.421 (3.97) [1.000]	-0.435 (-3.48) [-0.703]
Aggressive driving indicator (1 if the respondent thinks that s/he normally drives not aggressively, 0 otherwise)	-0.435 (-3.48) [-0.703]	0.439 (3.77) [1.000]

Table 6. Elasticities and pseudo-elasticities of the variables included in model specifications (N=584)

Variable	Bivariate probit		Bivariate probit		Binary probit
	Likelihood of relocating to city center	Likelihood of relocating to urban area (outside city center)	Likelihood of relocating to suburban area	Likelihood of relocating to rural area	Likelihood of not relocating at all
Socio-demographic characteristics					
Age of the respondent	-0.008	-0.006	-0.005	-0.002	0.004
Current neighbourhood indicator (1 if the respondent is currently living suburban or rural area, 0 otherwise)	-0.130	-0.113	–	–	–
Ethnicity indicator (1 if the respondent is Caucasian, 0 otherwise)	-0.085	-0.117	–	–	–
Ethnicity indicator (1 if the respondent is Asian, 0 otherwise)	–	–	0.062	–	–
Childhood living area indicator (1 if the respondent grew up in urban area, 0 otherwise)	–	–	–	–	-0.138
Opinions and Preferences					
Vehicle safety features indicator (1 if the respondent is familiar with adaptive cruise control feature, 0 otherwise)	–	–	–	–	0.157
Vehicle safety features indicator (1 if the respondent is familiar with left turn assist feature, 0 otherwise)	0.089	0.110	–	–	–
Cost benefit indicator (1 if the respondent thinks that lower vehicle maintenance cost is likely to occur with the introduction of flying cars, 0 otherwise)	0.138	–	–	–	–
Environmental benefit indicator (1 if the respondent thinks that less CO2 emission is likely with the introduction of flying cars, 0 otherwise)	–	–	0.058	0.143	–
In-vehicle activity indicator (1 if the respondent thinks more in-vehicle non-driving activities are likely, 0 otherwise)	–	–	–	–	0.159
Willingness to use indicator (1 if the respondent is willing to use flying cars for 50-100 mile long trips, 0 otherwise)	–	–	0.094	0.230	–
Willingness to use indicator (1 if the respondent is willing to use flying cars for airport access trips, 0 otherwise)	0.107	0.151	–	–	–

Variable	Bivariate probit		Bivariate probit		Binary probit
	Likelihood of relocating to city center	Likelihood of relocating to urban area (outside city center)	Likelihood of relocating to suburban area	Likelihood of relocating to rural area	Likelihood of not relocating at all
Security measure indicator (1 if the respondent thinks that using existing FAA regulations for air traffic control is very likely to improve security against hackers/terrorists, 0 otherwise)	—	0.091	—	—	—
Security measure indicator (1 if the respondent thinks that using existing FAA regulations for air traffic control is likely to improve security against hackers/terrorists, 0 otherwise)	—	—	—	0.159	0.055
Security measure indicator (1 if the respondent thinks that establishing air-road police enforcement – with flying police cars – is likely to improve security against hackers/terrorists, 0 otherwise)	—	—	0.047	—	—
Speed limit opinion indicator (1 if the respondent disagrees with the statement: “Speed limits on high speed freeways should only be suggestive”, 0 otherwise)	—	—	—	—	-0.167
Aggressive driving indicator (1 if the respondent thinks that s/he normally drives not aggressively, 0 otherwise)	—	—	—	—	-0.122

“—” : Variables that were not included in the corresponding model.

Appendix

A1. Information session on Flying Cars

To introduce the concept of flying cars to the respondents, a concise information session on flying cars preceded the survey as follows:

UB Survey

Flying Cars

By 2025 flying cars will likely be a new transport mode. A typical flying car model will:

- drive on the roads and highways;
- have a 500-mile flying cruise range;
- cruise at 200 miles per hour;
- require a 100 feet radius for vertical take-off/landing (there is no need for a runway);
- carry up to four passengers including the operator;
- require substantially less training time than a traditional pilot's license or sport pilot certificate;
- run on premium unleaded automotive gasoline;
- have a full vehicle parachute along with all modern automotive safety features including autonomous/self-driving capabilities; and
- be priced as a high-end luxury car.

Figure A1 Information session on flying cars

A2. Correlation matrix for selection of dependent variable pairs

“Table A2 Correlation matrix for selection of dependent variable pairs (t-stat in parentheses)

		Likelihood of relocating to:			
		City centre	Urban area	Suburban area	Rural area
Likelihood of relocating to:	City centre	–	0.791 (17.72)	0.303 (3.76)	0.214 (2.56)
	Urban area	0.791 (17.72)	–	0.652 (11.88)	0.423 (5.99)
	Suburban area	0.303 (3.76)	0.652 (11.88)	–	0.680 (13.65)
	Rural area	0.214 (2.56)	0.423 (5.99)	0.680 (13.65)	–