*Risk preference and adoption of autonomous vehicles*



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# Risk Preference and Adoption of Autonomous Vehicles

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## ABSTRACT

Despite an increasingly large body of research that focuses on the potential demand for autonomous vehicles (AVs), risk preference is an understudied factor. Given that AV technology and how it will interact with the evolving mobility system are highly risky, this lack of research on risk preference is a critical gap in current understanding. By using a stated preference survey of 1,142 individuals from Singapore, this study achieves three objectives. First, it develops one measure of psychometric risk preference and operationalizes prospect theory to create two economic risk preference parameters. Second, it examines how these psychometric and economic risk preferences are associated with socioeconomic variables. Third, it analyzes how risk preference influences the mode choice of AVs. The study finds that risk preference parameters are significantly associated with socioeconomic variables: the elderly, poor, females, and unemployed Singaporeans appear more risk-averse and tend to overestimate small probabilities of losses. Furthermore, all three risk preference parameters contribute to the prediction of AV adoption. These modeling results have policy implications at both the aggregate and disaggregate levels. At the aggregate level, people misperceive probabilities, are overall risk-averse, and hence under-consume AVs relative to the social optimum. At the disaggregate level, the elderly, poor, female, and unemployed are more risk-averse and thus are less likely to adopt AVs. These results suggest that it might be valuable for governments to implement policies to encourage technology adoption, particularly for disadvantaged social groups, although caution remains due to uncertainty in the long-term effects of AVs. Individualized risk preference parameters could also inform how to design regulations, safety standards, and liability allocations of AVs since many regulations are essentially mechanisms for risk allocation. One limitation of the paper is that risk preference is measured and modeled only as individual-specific but not alternative-specific variables. Future studies should examine the relationship between the multiple components of risk preference and the multiple risky aspects of AVs.

**Keywords**: risk preference; autonomous vehicles; prospect theory; stated preference; Singapore

## INTRODUCTION

Autonomous vehicles (AVs) promise to trigger a revolution in urban transportation systems. To prepare for this important and emerging technology, researchers have begun to analyze the factors that influence AV adoption. Many of these studies use stated-preference surveys, in which AVs are incorporated as an additional alternative to current travel modes. These studies generally include socioeconomic attributes of individuals and lifestyle factors to explain AV mode choice.

However, one factor that may strongly influence AV adoption is *risk preference*, which is understudied in recent AV literature. Risk preference is particularly germane to AV adoption because both AV technology and its interactions with mobility systems are highly risky. In fact, risk preference is a critical factor in any new technology since risk preference determines consumer behavior and individual responses to policy and market conditions. This connection between risk preference and technology adoption has been widely discussed in the contexts of economic development, equity, entrepreneurship, policy design, insurance policies, and risk management (Liu, 2013; Mosley & Verschoor, 2005; Nicholson & Snyder, 2011). For example, risk-averse people are less willing to adopt new technology or invest in businesses involving risk (Mosley & Verschoor, 2005). Thus, researchers have argued that policy makers need to allocate risk by designing public policies and safety standards that take into account both technology risk and people's risk preferences (Nicholson & Snyder, 2011). In the transportation field, researchers have discussed how risk preferences are associated with sustainable travel behavior (Elias & Shiftan, 2012), the choice between risky bus operation contracts (Hensher et al., 2016), and underinvestment in the vehicle fuel economy (Greene et al., 2008). The public has a genuine concern about the safety and reliability of AVs, which are inherent risk factors associated with each individual's risk preference (Kyriakidis et al., 2015). While both AVs and risk preference have been researched intensively, their relationship is understudied in spite of their intuitive connection.

*To fill this gap, this study seeks to (1) measure individual risk preference by using psychometric and economic methods based on prospect theory (PT); (2) examine how risk preference is associated with socioeconomic status; and (3) analyze how economic and psychometric risk preference is associated with the mode choice of AVs.* These three objectives are examined in Model Groups 1, 2, and 3, respectively, as visualized in Figure 1. Although our focus is the third objective probing the link between risk preference and AV mode choice, the first objective is prerequisite of the third, and the second objective examines heterogeneity of risk preference, which is important in policy discussions. Model Group 1 extracts two economic risk preference parameters: probability weighting parameter ($\alpha$) and value function based risk preference parameter ($\beta$), by using individualized linear regressions and utility functions based on PT. Model Group 1 also extracts one psychometric risk-seeking parameter ($\gamma$) using factor analysis. Model Group 2 regresses these three risk preference parameters on socioeconomic variables, examining the variation of risk preference in the sample. Model Group 3 comprises mixed logit choice models, with AVs and four other travel modes as dependent variables, three risk preference parameters as the independent variables of interest, and others as controls. The three model groups were estimated sequentially rather than simultaneously[1].

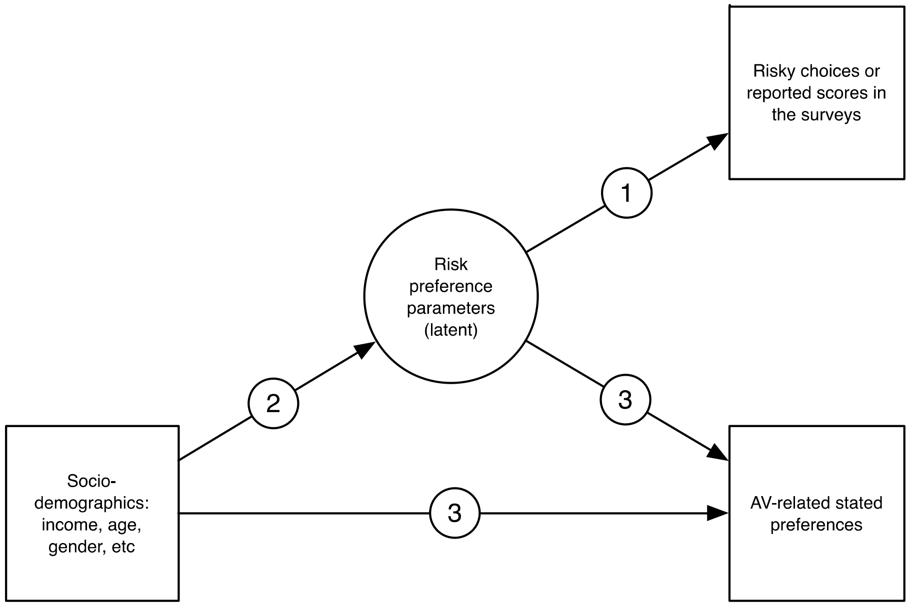


**Figure 1 Structure of the three Model Groups**

It is critical to differentiate between Model Groups 1 and 3 because both involve choice and utility. Model Group 1 examines the hypothetical choice between generic monetary payoffs, while Model Group 3 examines the choice among specific travel mode alternatives in a standard stated preference (SP) survey. As a result, the risk preference parameters obtained through generic monetary payoffs are specific to individuals but generic in choice context. Hence, this paper examines only the impact of risk preference on the choice of AV relative to other transportation modes. It does not model the specific risky aspects of AVs, such as accidents, time reliability, and travel cost risks; nor does it intend to differentiate the sources of the risks related to AVs, such as policy, technology, and market. In other words, this paper treats risk preference parameters as individual-specific, rather than travel mode specific. Individual-specific variables are common in choice models, and this method of eliciting generic risk preference and applying them to concrete contexts has been widely used in the literature (Kam, 2012; Liu, 2013; Tanaka et al., 2010). Furthermore, individualized risk preference parameters are necessary owing to their heterogeneity across the population (De Palma et al., 2008).

To support these models, a questionnaire survey was designed and disseminated to 1,142 people in Singapore to obtain their risk preferences, socioeconomic status, and choices for AV use under seven scenarios. The data were used to construct individualized risk preference parameters and to

[1] Model Groups 2 and 3 can potentially be estimated simultaneously; however, Model Group 1 cannot. Edge 1 represents the models measuring individualized economic and psychometric risk preference parameters and consists of 1,142 individualized linear regressions used to obtain 2,284 economic risk preference parameters. Edge 3 is a mixed logit model, which requires simulated maximum likelihood estimation. No standard software package could accommodate these three model groups. Sequential estimation does not create bias problems in a graph with full observations, although the estimated covariance could be inaccurate.

build a choice model analyzing how risk preference influences the adoption of AVs. Singapore was chosen as the study case because of its pioneering role in developing and adopting AVs.

It is also important to clarify two differences between risk and uncertainty in academic and colloquial settings. In formal academic literature, risky events are those with known probabilities, whereas uncertain events refer to those without clear probability measures (Knight, 1921; Tversky & Fox, 1995). Associated with this distinction, risk aversion and uncertainty aversion are two different types of risk attitudes (Tversky & Fox, 1995). In colloquial use, on the other hand, risk has a negative connotation while uncertainty is neutral. Risk implies only losses, while uncertainty relates to either gains or losses. For example, a layperson saying that AVs are risky, implicitly refers to the potential dangers or losses involved in AVs, while the positive uncertain aspects of risks, such as technology improvement, are not included. This paper mainly uses the academic rather than colloquial concept of risk because Model Group 1 explicitly incorporates probability numbers. Therefore, in this paper, “risky dimensions of AVs” refer to both the positives (e.g., time saving benefits) and the negatives (e.g., safety concerns) of AVs. In addition, when the broad concept of uncertainty is used, it refers to both the measurable and immeasurable uncertainty of AVs.

This research contributes to both behavioral understanding of AV preference and general studies of risk. First, with regard to behavioral research of AV preference, our results illustrate the importance of risk preference as a determinant of AV adoption. PT is operationalized to measure individualized risk preference, which is further used in the choice models for policy analysis. Second, for risk-related studies in general, this research compares the economic and psychometric methods of gauging risk preference and analyzes their different impacts on AV use. The following sections of this paper build these contributions by discussing relevant studies and then presenting our methodology, data collection, results, and final conclusions.

## LITERATURE REVIEW

This literature review consists of three parts. The first part reviews studies related to AV adoption. The second part reviews studies related to risk, including decision-making under uncertainty and the psychometric and economic measurements of risk preference. The third part reviews behavioral and policy discussions related to risk preference.

### Autonomous Vehicles

Studies about AVs can be sorted into three categories: behavioral, operational, and policy analyses. Behavioral analyses examine who will adopt AVs: in particular, how much people are willing to pay and how socioeconomic factors are associated with AV-related decisions, such as intended use and ownership (Daziano et al., 2017; Krueger et al., 2016; Yap et al., 2016). Operational analyses examine how to assign AV lanes or zones to achieve the social optimum, or simply to stabilize travel flows when AVs and conventional vehicles are mixed (D. Chen et al., 2017; Z. Chen et al., 2017; De Oliveira, 2017). Policy analyses focus on the impacts, benefits, costs, barriers, and possible development scenarios and policy responses related to AVs (Fagnant & Kockelman, 2015; Kyriakidis et al., 2015; Lamotte et al., 2017; Mersky & Samaras, 2016). For example, Fagnant and Kockelman (2015) enumerate the potential benefits of AVs—such as improving vehicle safety, mitigating congestion, reducing crashes, lessening travel time, and increasing fuel efficiency—and barriers to their adoption—such as inconsistent state licensing and testing standards, undefined liability details, unclear security concerns, and a default lack of privacy for personal travel. Milakis et al. (2015) identified future development paths of AVs in the Netherlands and estimated potential implications for traffic, travel behavior, and transport planning up to 2030 and 2050.

Among the three categories, behavioral analyses are the most germane to our study. While these studies share similar research objectives, they draw from distinct research perspectives. Yap et al. (2016) analyzed preferences for using AVs to travel the last mile, with the assumption that AVs could effectively contribute to solving the last mile problem. Krueger et al. (2016) focused on AV users who are most likely to share rides, assuming that AVs can more effectively and efficiently facilitate ride sharing. Goncalo de Almeida Correia et al. (2019) found that riders have lower value of time when taking AVs with an office interior, as opposed to the conventional car. From a sample of 5000 individuals in a wide array of countries, Kyriakidis et al. (2015) found that the public was mostly concerned with software hacking, legal issues, and safety when it came to the adoption of AV technology. Bansal and Kockelman (2017) focused on the long-term adoption of AVs, with assumptions involving cost, willingness to pay (WTP), and policy changes. Despite their various perspectives, these studies are similar in that most use discrete choice models with data based on SP surveys. SP surveys are necessary because AVs are not in widespread use, so very limited revealed preference (RP) data are available.

The studies focused on demand of AVs have also illustrated how socioeconomic variables can account for AV adoption. Yap et al. (2016) found that first-class train travelers would be more likely to use AVs for the last mile from public transit stations to home. Krueger et al. (2016) concluded that young individuals and individuals with multimodal travel patterns would be more likely to use shared AVs. Bansal and Kockelman (2017) concluded that non-drivers, the elderly, and people with travel-restrictive medical conditions would be most influenced by AVs. Haboucha et al. (2017) argued that young people, students, and more educated people would be more likely to use AVs. Evidently, common socioeconomic variables, such as income, age, education, health, and gender, should be included in our study.

Beyond these socioeconomic variables, many studies have investigated the importance of public opinion, personality measures, and attitudes in determining the adoption of AVs. Haboucha et al. (2017) used factor analysis to extract latent attitudes—including technology interests, environmental concerns, driving enjoyment, public transit attitude, and pro-AV sentiments— and used them to explain AV adoption behavior. Kyriakidis et al. (2015) found that perceived safety and reliability relate to the decision of using or owning AVs. Yap et al. (2016) found that perceptions of trust and sustainability of AVs were significant predictors of AV adoption, prompting the authors to conclude that further studies should pay more attention to psychometric factors. It is no surprise that psychometric factors are critical, since they have long been used in choice modeling for predicting travel behavior (Morikawa et al., 2002).

In addition to these and similar studies that focus on the demand side, at least a dozen other studies focus on operational or policy perspectives to enrich our understanding of the overall impact of AVs. These studies generally focus on how to (1) effectively allocate road capacity to improve social welfare; (2) deploy AV lanes with concerns for an endogenous market penetration process; (3) dynamically assign AVs to reduce generalized transportation costs or mitigate congestion with the reallocation of empty vehicles; (4) help city governments prepare for the upcoming challenges posed by AVs; and (5) determine how connected and automated vehicles influence traffic stability and throughput (D. Chen et al., 2017; Z. Chen et al., 2017; Chen et al., 2016; De Almeida Correia & Van Arem, 2016; Freemark et al., 2019; Guerra, 2016; Talebpour & Mahmassani, 2016). While these studies are critical for informing policymakers and the market about upcoming AVs, they are not the most relevant to our analysis.

**Risk Preference**

Risk is a prevalent feature in numerous choice scenarios. For example, risk is involved in voting decisions because one vote is highly unlikely to change the election result (Kam, 2012). Risk is involved in anti-terrorism decisions because the next terrorism attack could occur at any time and in any place (Sunstein, 2003). To understand the characteristics of decision-making under risk, scholars from various fields have been building theories and working on methods of eliciting risk preference parameters. Thus far, these methods can be grouped into psychometric or economic approaches.

The psychometric approach usually uses the self-reported propensity of risky behaviors to measure risk preference. For example, in the study of voting behaviors, a measure of risk was derived from a series of 5-point Likert scale statement such as, “I would like to explore strange places” (Kam, 2012). In the transportation field in particular, this approach has been predominantly applied to analyze risky driving behaviors. Starkey and Isler (2016) found that psychometric risk preference parameters contribute to explaining self-reported risky driving behaviors, such as the number of crashes, driving-related convictions, and traffic warnings the driver received. Harbeck et al. (2017) found that risk preference scores can partially explain speeding, drunk or drug-impaired driving, seatbelt use, fatigued or distracted driving, mobile (cell) phone use while driving, tailgating, and red traffic light violations. In these studies, the psychometric risk preference parameters are often extracted using factor analysis (Harbeck et al., 2017; Kam & Simas, 2012; Starkey & Isler, 2016).

Alternatively, the economic approach to elicit risk preference can be based on either an expected utility (EU) framework or a prospect theory (PT) framework, with the latter being recommended because it addresses the Allais paradox (Allais, 1953; Kahneman & Tversky, 1979; Neumann & Morgenstern, 1944). In the PT framework, a utility function takes a product-sum form, $U(x) = \sum w(p_i)v(x_i)$, in which $x$ represents a prospect consisting of several payoffs $x_i$ and associated probabilities $p_i$; $v(x_i)$ takes a concave form; and probability weighting function $w(p_i)$ is an S-shaped curve bounded between zero and one. Because the probability weighting function is a major contribution of PT to EU, Fehr-Duda and Epper (2012) summarized all functional forms of $w(p_i)$ and concluded that the probability weighting function in Prelec (1998) is most theoretically appealing (Goldstein & Einhorn, 1987; Prelec, 1998; Tversky & Kahneman, 1992). Moreover, the Prelec (1998) probability weighting function can be easily transformed into a linear form such that a simple linear regression can be applied to elicit individualized risk preference parameters. The details of the parameterization are illustrated in the methodology section of this paper.

It is difficult to conclude which of the two approaches—psychometric or economic—is universally better for measuring risk preference. In fact, there are strengths and weaknesses in both. The psychometric approach is more intuitive because the behavioral statements are readily interpretable and generally understandable for respondents. However, the behavioral questions based on the psychometric approach lack a generic standard. Conversely, the economic approach has a standard way to elicit risk preference parameters that can be readily incorporated into choice models. However, the behavioral implications of the risk preference parameters are complex, depending on the gains and losses and the range of probabilities. This can lead to difficulty in model interpretation. Hence, this study implements both approaches to acquire risk preference parameters in the context of AV mode choice.

### Behavioral and Policy Discussion about Risk Preference

Risk preference has gradually received more attention in the behavioral and policy analyses concerning the adoption of new technology, which is an important question in development economics, marketing, and transportation. (Liu, 2013) analyzed how cotton farmers in China decided to adopt new technology by using the risk preference parameters estimated by PT. Dupas (2014) traced the adoption of mosquito nets in Africa to analyze how local residents responded to the risks involved in a product they had never seen. Many policy regulations naturally involve decision under risks. For example, seat belt regulation and smoking regulation directly address potential risks (Camerer & Kunreuther, 1989). In the transportation domain, Xu and Fan (2018) discussed the risk perception of AVs and insurance premiums, suggesting that Chinese people hold a positive view about AVs, and expect lower risk and lower insurance premiums for AVs than for traditional automobiles. Elias and Shiftan (2012) and Wu and Nie (2011) discussed how risk preference is associated with other types of travel behavior, such as travel mode choice and route choice.

Recent studies in behavioral welfare economics connected risk preference directly to policy intervention. Behavioral welfare economics suggests that people produce negative externalities for themselves (and for the system) in the long-run, owing to their cognitive biases or myopic choices (Madrian, 2014). The expected value (EV) model is often used as a normative benchmark because the population could gain collectively in the long-run if they follow EV decision criteria in repeated risk choices. In the case of AVs, people may reject or delay AV use because they overestimate the small probability of a large loss, even when the expected value of AVs is positive. Consequently, due to risk-aversion, people might under-consume AVs, and some policy intervention can be justified to improve AV adoption. In fact, the same reasoning applies to underinvestment in vehicle fuel economy, as suggested by Greene et al. (2008).

## METHODOLOGY

### Model Group 1: Measure Economic and Psychometric Risk Preference Parameters

*Economic Risk Preference Parameters*

The economic risk preference parameters are represented by two parameters in the utility function based on PT (Kahneman & Tversky, 1979). The utility of a risky prospect takes the form:

$$U(x, p) = v(x; \beta) w(p; \alpha), \tag{1}$$

in which $x$ is the gain or loss of the risky prospect in the value function $v()$, and $p$ is the probability measurement in the probability weighting function $w()$. Notice the equation here is simplified because the attributes of the risky prospect were presented as indifferent pairs in our survey. Normally, the utility function should be the sum of several equations taking the form of Equation 1. Economic risk preference parameters are the probability weighting parameter $\alpha$ in $w()$ and the curvature parameter of the value function $\beta$ in $v()$. These individualized economic risk preference parameters can be derived from responses to several indifferent pairs of prospects $k$ for each individual $i$. Specifically, when the person feels indifferent between the sure $y_{ik}$ gain and a prospect consisting of $x_{ik}$ payoff with probability $p_{ik}$ and 0 payoff with probability $1 - p_{ik}$, denoted as $y_{ik} \sim (x_{ik}, p_k; 0, 1 - p_k)$, one can use the indifferent pairs to compute economic risk preference parameters $\alpha_i$ and $\beta_i$. Formally, the value function with the power form and Prelec (1998) probability weighting function imply

$$U(x_{ik}, p_{ik}) = \mathrm{x}_{\mathrm{ik}}^{\beta_i} \, exp(-(-\, ln\, p_{ik})^{\alpha_i}) \tag{2}$$

$$U(y_{ik}) = y_{ik}^{\beta_i} \tag{3}$$

$$U(x_{ik}, p_{ik}) = U(y_{ik}), \forall i, k \tag{4}$$

By inserting the values of Equation 2 and 3, a simple transformation of Equation 4 yields the following linear regression:

$$log\left(log\left(\frac{x_{ik}}{y_{ik}}\right)\right) = -\, log(\beta_i) + \alpha_i \, ln(-\, ln\, p_{ik}) + \epsilon_{ik}, \forall i, \tag{5}$$

in which $i$ indicates each individual, and $k$ is the index representing indifferent pairs ($\mathrm{k} = 1, 2, 3, 4$). This regression[2] in Equation 5 helps to derive the individualized economic risk preference parameters ($\alpha_i$, $\beta_i$) for each participant $i$ in Model Group 1. A simple intuition is that $\alpha_i$ relates to very small and large probabilities, while $\beta_i$ relates to more middle-range probabilities (see Appendix I). Note that Equation 2 could be reduced to an expected value (EV) utility function $U(x_{ik}, p_{ik}) = x_{ik} p_{ik}$, when $\beta_i = 1$ and $\alpha_i = 1$. The EV utility function is used as a normative benchmark, because the utility function based on PT describes irrational behavioral characteristics, deviating from the normative optimum. EV is normatively optimal because people could gain benefits in repeated gambling games by following EV, while they could lose money by following PT.

[2] Note that this individualized regression uses only four observations to compute two parameters; hence, the regressions do not satisfy the large sample assumption and normal distribution assumption. It should be treated as a process of calculating measurements with prospect theory and using mean squared error as the objective to be minimized. Composite variables $\alpha_i$ and $\beta_i$ are based on prospect theory, and they have neither consistency nor asymptotical normality, as typically derived in linear regression.

One important question is how to use surveys to elicit the indifferent pairs $y_{ik} \sim (x_{ik}, p_k; 0, 1 - p_k)$. To elicit the indifferent pairs, our survey uses the certainty-equivalent (CE) method (Gonzalez & Wu, 1999; Tversky & Kahneman, 1992). The CE method means that given a risky prospect $(x, p; 0, 1 - p)$, respondents state a sure gain $y$, which makes them indifferent between the two prospects. In our survey, people were asked to provide a CE for each of the four risky prospects with varying probabilities listed in the top panel of Table 1. For example, in Lottery 1, $(x_{ik}, p_k; 0, 1 - p_k)$ was provided as $(\$10{,}000, 1\%; \$0, 99\%)$, and the respondent $i$ stated the sure amount of money $y_{ik}$ that made him or her indifferent from $(\$10{,}000, 1\%; \$0, 99\%)$. Four indifferent pairs for each individual were used to estimate the two economic risk preference parameters $\alpha_i$ and $\beta_i$.

**Table 1 Questions used to measure economic and psychometric risk preferences**

| |
|---|
| **Economic Method Used to Measure $\boldsymbol{\alpha_i}$ and $\boldsymbol{\beta_i}$** |
| • Lottery 1 ($k = 1$): This lottery offers a 1% chance of winning \$10,000 and a 99% chance of winning \$0. What sure amount of money would make you equally happy as entering this lottery?<br>• Lottery 2 ($k = 2$): This lottery offers a 15% chance of winning \$10,000 and a 85% chance of winning \$0. What sure amount of money would make you equally happy as entering this lottery?<br>• Lottery 3 ($k = 3$): This lottery offers a 75% chance of winning \$10,000 and a 25% chance of winning \$0. What sure amount of money would make you equally happy as entering this lottery?<br>• Lottery 4 ($k = 4$): This lottery offers a 99% chance of winning \$10,000 and a 1% chance of winning \$0. What sure amount of money would make you equally happy as entering this lottery? |
| **Psychometric Method Used to Measure $\boldsymbol{\gamma_i}$** |
| Consider the following statements. For each statement, rate your agreement with it on a scale from 1 to 7, where 1 is "Strongly disagree" and 7 is "Strongly agree".[3]<br>• In general, it is difficult for me to accept taking risks. [Score reversed]<br>• I like new and exciting experiences, even if I have to break the rules.<br>• I am very cautious about making major changes in my life. [Score reversed] |

*Psychometric Risk Preference Parameters*

The psychometric measure is computed from three self-reported questions listed in the bottom panel of Table 1, which were chosen based on Kam (2012). Factor analysis was used to extract one underlying psychometric risk-seeking parameter $\gamma_i$. This psychometric risk-seeking parameter is assumed to be a Gaussian distribution with its mean normalized to 0. Hence, the relative comparison of $\gamma_i$ has a behavioral interpretation: a larger $\gamma_i$ indicates greater preference for riskier behaviors.

[3] The preprocessing of factor analysis reversed the scores of Questions 1 and 3 to make the direction of the scores of the three questions consistent.

**Methods of Model Group 2: Linear Regressions of Risk Preference on Socioeconomic Variables**

Model Group 2 analyzes the association between the three risk preference parameters and each individual's socioeconomic variables. These models are estimated as simple linear regressions as expressed by Equations 6, 7, and 8:

$$\alpha_i = \sum_j t_{\mathrm{j}}^{\alpha} z_{ij} + \epsilon_{\alpha_i} \tag{6}$$

$$\beta_i = \sum_j t_{\mathrm{j}}^{\beta} z_{ij} + \epsilon_{\beta_i} \tag{7}$$

$$\gamma_i = \sum_j t_{\mathrm{j}}^{\gamma} z_{ij} + \epsilon_{\gamma_i} \tag{8}$$

In the equations above, $z$ is the vector of socioeconomic variables indexed by $j$ for each individual $i$, $\epsilon$ is the random error term, and $t_j^{\alpha}$, $t_j^{\beta}$, and $t_j^{\gamma}$ are the coefficients of interest, which reveal the socioeconomic characteristics of risk-seeking and risk-averse people.

**Methods of Model Group 3: AV Mode Choice Model**

The three risk factors $\alpha_i$, $\beta_i$, and $\gamma_i$ are then included in the utility functions of a classic mixed logit discrete choice model in order to test the statistical significance of and interpret the coefficients $a_{\alpha}$, $a_{\beta}$, and $a_{\gamma}$ (see Equation 9). It is worth noting that the utilities in Equation 9 describe the utilities of choosing a travel mode, represented by Edge 3 in Figure 1, which differ from the utilities used to elicit economic risk preference represented by Edge 1 in Figure 1. Formally, the utility functions of Model Group 3 are:

$$U_{ik} = a_{\alpha}\alpha_i + a_{\beta}\beta_i + a_{\gamma}\gamma_i + \sum_m t_{\mathrm{mk}} x_{imk} + \sum_j t_{\mathrm{j}} z_{ij} + \epsilon_i + \omega_k + \delta_{ik}\,, \tag{9}$$

where $i$ denotes the index of respondents; $k$ is the index of alternatives, including AVs, ridesharing, driving, buses, and walking; $j$ is the index of individual-specific variables, such as income, education, and age; $m$ is the index of alternative-specific variables, such as travel cost, walking time, waiting time, and in-vehicle travel time; $U_{ik}$ is the utility of alternative $k$ for individual $i$; $\sum_m t_{\mathrm{mk}} x_{imk}$ is the linear combination of alternative-specific variables; and $\sum_j t_{\mathrm{j}} z_{ij}$ is the linear combination of individual-specific variables. $a_{\alpha}$, $a_{\beta}$, and $a_{\gamma}$ are the coefficients of the three risk preference parameters, which are the major interest of this study; $\epsilon_i$ is the individual specific random error, which takes into account the unobserved individual heterogeneity; $\omega_k$ is the mixed logit model parameter that captures the correlation across alternatives, assumed to be normally distributed; and $\delta_{ik}$ is the random utility error term that is assumed to follow the extreme value distribution.

## SURVEY DESIGN AND DATA COLLECTION

In July 2017, a total of 1,989 participants were recruited to complete an online questionnaire in Singapore via a professional survey company, Qualtrics. From these initial 1,989 responses, we excluded individuals who did not answer questions related to risk preference, acknowledged that they could not understand the risk preference questions in the survey,[4] or did not report consistent risk preferences across the four indifferent pairs. This left us with a final sample size of 1,142 individuals for all of our analysis.

The age of the participants ranged between 20 and 85, and the income ranged from no income to over $20,000 per month. A comparison of age and income distribution between the sample and the population is summarized in Table 2. In terms of age, the sample overrepresents young people, and underrepresents the elderly. In terms of monthly income, individuals with no income and very high income (more than S$20,000) are underrepresented in the sample, while the distribution of all other income groups was close to that of the population. All participants received monetary compensation for their responses.

**Table 2 Comparison of sample and population age and income distribution (N=1,989)**

| Age Group | Population (%) | Sample (%) | Income Group | Population (%) | Sample (%) |
|---|---|---|---|---|---|
| 20–24 | 8.42 | 16.31 | No income | 10.79 | 1.46 |
| 25–29 | 9.04 | 17.32 | Below $2,000 | 7.49 | 7.19 |
| 30–34 | 9.22 | 15.45 | $2,000–$3,999 | 10.69 | 14.90 |
| 35–39 | 9.75 | 14.08 | $4,000–$5,999 | 11.29 | 17.35 |
| 40–44 | 10.12 | 10.09 | $6,000–$7,999 | 10.89 | 15.57 |
| 45–49 | 9.72 | 10.20 | $8,000–$9,999 | 9.49 | 14.77 |
| 50–54 | 10.19 | 7.42 | $10,000–$11,999 | 8.39 | 10.07 |
| 55–59 | 9.67 | 4.93 | $12,000–$14,999 | 9.09 | 8.22 |
| 60-64 | 8.13 | 2.49 | $15,000–$19,999 | 9.49 | 4.78 |
| 65–69 | 6.39 | 0.67 | Over $20,000 | 12.39 | 5.69 |
| 70–74 | 3.35 | 0.91 | | | |
| 75–79 | 2.84 | 0.00 | | | |
| 80–84 | 1.73 | 0.13 | | | |
| 85+ | 1.43 | 0.00 | | | |

The survey consisted of one section each for RP, SP, and for eliciting the socioeconomic status and risk preference of the participants. The survey started with the RP section, in which all respondents reported the postal codes of their home and working locations, and their current travel mode. From respondent home (origin) and work (destination) locations, we computed the walking time, waiting time, in-vehicle travel time, and travel cost of each travel mode for each individual's commute trip using Google Maps API. Price information was collected from official data sources in Singapore. The information gathered from the RP section was then used to automatically generate the SP section, which was the bulk of the questionnaire. The AV mode

[4] The questionnaire explicitly asked the respondents whether they could understand these questions to help filter out invalid responses.

was introduced in the SP section for a total of five travel modes choices: walking, public transit, driving, ride sharing, and AVs. The survey specified the AV mode as a fleet-based shared mobility service, as this is the form of AV deployment being piloted in Singapore. There are clearly other deployment forms, such as privately-owned AVs; however, they are not considered in this survey. The SP section followed the standard method of orthogonal design (Louviere et al., 2000). Each attribute took three levels of values with the medium equal to the value revealed in the RP section so that the values were realistically anchored and readily understandable to participants. The other two levels were adjusted by multiplying the medium value by certain constants. The value range of the AV travel time and cost resembled that of the ride-sharing mode. The final completed SP section contained 54 combinations of attribute values from which seven were randomly picked and presented to each respondent.

The last section of the survey elicited the crucial information to measure risk preference parameters, including the four indifferent pairs of economic risk assessments and the three indicators of psychometric risk measures as shown in Table 1. Basic socioeconomic information such as gender, education, and income were also collected at this stage. The four indifferent pairs of economic risk measures were used as inputs into Equation 5 to compute two economic risk preference parameters. The three psychometric indicators were used to compute one psychometric risk preference parameter. All economic and psychometric risk preference parameters were used in Model Group 2 as dependent variables and in Model Group 3 as explanatory variables. Socioeconomic variables were used as explanatory variables in Model Group 2 and as control variables in Model Group 3.

## RESULTS

The results section will show the results of Model Groups 1, 2, and 3, respectively. The section starts with the results of Model Group 1, which extracts risk preference parameters. Next, we consider Model Group 2, which explores what sociodemographic characteristics help determine an individual's risk preference parameters. Finally, Model Group 3 is presented, which captures the impact of risk preference parameters on travel mode choice. This section only emphasizes the components directly related to risk preference parameters while omitting discussion of other estimated coefficients and their implications, such as value of time and taste heterogeneity.

### Model Group 1: Risk Preference Parameters Elicited by the Economic and Psychometric Methods

Individualized economic risk preference parameters were derived from 1,142 linear regressions (one for each person using his/her four indifferent pairs). The derived risk parameters have considerable heterogeneity across individuals (see panel 1 of Table 3). Considering the economic risk parameters, the median values of $\alpha$ and $\beta$ are both smaller than 1 (0.882 and 0.907, respectively), consistent with the theory that a representative individual tends to overestimate small probabilities ($\alpha < 1$) and has a concave utility function ($\beta < 1$). However, the heterogeneity of each risk parameter is large. In addition, the distribution of $\alpha$ is segmented into two ranges: one smaller than 2 and the other larger than 2 (see Appendix I). The parameter $\beta$ is also not homogeneous: it has a broad and skewed distribution with a very long right tail. The considerable heterogeneity echoes the importance of using individualized risk preference parameters in choice models. Additionally, factor analysis is used to extract the psychometric risk parameter, $\gamma$. The factor loadings of the psychometric risk parameters are (0.91, 0.47, 0.70). The following choice models use the factor score $\gamma$, instead of the three raw psychometric indicators. The detailed distribution of $\alpha$, $\beta$, and $\gamma$ is attached in Appendix I.

Panel 2 in Table 3 shows two patterns from the correlation matrix of $\alpha$, $\beta$, and $\gamma$. First, the economic risk parameters have almost no correlation with the psychometric risk parameter. The two approaches seem to capture very different aspects of risk-related behavior, although they are both purport to measure the same concept of risk preference. Second, the two economic risk preference measures are correlated. The positive correlation between $\alpha$ and $\beta$ implies that people are likely to follow concurrently the classic theories of probability weighting functions and utility functions, namely, overestimating small probabilities and having concave utility curves in gains. Geometrically, this implies that a concave utility function and a typical S-shaped probability weighting function often emerge simultaneously.

Panel 3 in Table 3 compares the average values of the risk preference parameters across the individuals who chose the five different modal alternatives. Respondents who chose AVs had the second highest $\alpha$, $\beta$, and $\gamma$, and those choosing driving had the highest $\alpha$, $\beta$, and $\gamma$, suggesting a certain degree of association between risk preference and mode choice, before controlling for socioeconomic and travel variables.

**Table 3 Descriptive statistics of alpha, beta, and gamma**

| Panel 1 Summary statistics for the whole dataset (N = 1,142) | | | |
|---|---|---|---|
| | Alpha | Beta | Gamma |
| Mean | 1.522 | 1.863 | 0.000 |
| Standard deviation | 1.184 | 2.742 | 0.786 |
| Minimum | 0.001 | 0.075 | -1.935 |
| 25th percentile | 0.476 | 0.387 | -0.541 |
| 50th percentile | 0.882 | 0.907 | -0.055 |
| 75th percentile | 2.889 | 2.159 | 0.533 |
| Maximum | 3.279 | 34.547 | 2.873 |
| **Panel 2 Correlation matrix** | | | |
| | Alpha | Beta | Gamma |
| Alpha | 1.000 | 0.464 | 0.013 |
| Beta | 0.464 | 1.000 | 0.051 |
| Gamma | 0.013 | 0.051 | 1.000 |
| **Panel 3 Mean comparison across five mode choices** | | | |
| Respondents' Choice | Alpha | Beta | Gamma |
| AV | 1.594 | 2.201 | 0.024 |
| Bus | 1.469 | 1.781 | -0.047 |
| Drive | 1.659 | 2.224 | 0.081 |
| Ride-sharing | 1.490 | 1.997 | 0.012 |
| Walk | 1.591 | 1.710 | 0.001 |

**Model Group 2: Determinants of Risk Preference Parameters**

Table 4 summarizes the six models analyzing how risk preference parameters are associated with socioeconomic variables using the cleaned sample of 1,142 individuals. Models 1 and 2 are linear regressions of $\alpha_i$; Models 3 and 4 are of $\beta_i$; and Models 5 and 6 are of $\gamma_i$. Models 1, 3, and 5 use age, education, and income as continuous variables, whereas Models 2, 4, and 6 transform these socioeconomics into discrete variables to capture potential nonlinear relationships.

The signs of the coefficients are intuitive and consistent with past studies on risk preference both in and outside the transportation domain. In terms of $\alpha$, Models 1 and 2 suggest that males and fully-employed people tend to underestimate small probabilities, and older people tend to overestimate small probabilities. Hence, if an event involves small risks with large losses, males are more likely to choose it, while older people are less likely to do so. In terms of $\beta$ (the curvature parameters of the value function), Models 3 and 4 suggest that older males tend to report smaller values, implying that they are less likely to choose an event with some positive gains. On the other hand, fully employed people are more likely to choose an event with some positive gains, as the coefficient of employment is positive in predicting $\beta$. In terms of $\gamma$, Models 5 and 6 suggest that males and those with higher-incomes and higher educational attainment tend to have higher psychometric risk-seeking parameters.

Suppose a new technology involves some positive gains and potentially large losses with very small probabilities. In such a case, our models suggest that young, high-income, fully-employed people with higher education could be more likely to adopt it than the average individual, while low-income, older, and unemployed people could be less likely to do so.[5] In fact, these findings are consistent with the past analyses related to risk preference (Greene et al., 2008). Poor people are more risk-averse, leading to lower adoption of new technology, investment, and entrepreneurship. However, similar to several other studies (Tanaka et al., 2010), the low $R^2$ of all models indicates that the variation of risk preferences among individuals cannot be well explained by their socioeconomic status. Thus, risk preference requires its own dedicated measure (or set of measures) to be included in the following AV mode choice model.

**Table 4 Linear regression results**

| | **Regressions on alpha** | | **Regressions on beta** | | **Regressions on gamma** | |
|---|---|---|---|---|---|---|
| | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** | **Model 6** |
| Male | 0.153** | 0.158** | -0.368** | -0.342** | 0.175*** | 0.175*** |
| | (0.071) | (0.071) | (0.166) | (0.166) | (0.047) | (0.047) |
| Age | -0.010*** | | -0.004 | | 0.002 | |
| | (0.003) | | (0.006) | | (0.002) | |
| Education | -0.025 | | -0.085 | | 0.037* | |
| | (0.035) | | (0.08) | | (0.023) | |
| Income | 0.007 | | 0.024 | | 0.017*** | |
| | (0.007) | | (0.017) | | (0.005) | |
| Dummy (Age>60) | | -0.417*** | | -0.610* | | 0.009 |
| | | (0.155) | | (0.36) | | (0.102) |
| Dummy (Age<35) | | 0.190** | | 0.146 | | -0.058 |
| | | (0.075) | | (0.176) | | (0.05) |

[5] The gender effect is unclear because the coefficient for males is opposite for $\alpha$ and $\beta$

| | | | | | | |
|---|---|---|---|---|---|---|
| Dummy Low Education | | 0.037 | | 0.467 | | 0.051 |
| (Less than 9 Years) | | (0.139) | | (0.324) | | (0.091) |
| Dummy High Education | | -0.055 | | -0.163 | | 0.129** |
| (More than 16 Years) | | (0.079) | | (0.185) | | (0.052) |
| Dummy Low Income | | -0.307** | | -0.283 | | -0.145* |
| (< S$4,000/Year) | | (0.129) | | (0.301) | | (0.085) |
| Dummy High Income | | -0.024 | | 0.263 | | 0.111** |
| (> S$15,000/Year) | | (0.077) | | (0.178) | | (0.05) |
| Dummy Fulltime Job | 0.125 | 0.073 | 0.360* | 0.308 | 0.081 | 0.065 |
| | (0.084) | (0.087) | (0.196) | (0.203) | (0.055) | (0.057) |
| Constant | 1.810*** | 1.404*** | 2.104*** | 1.741*** | -0.537*** | -0.225*** |
| | (0.184) | (0.107) | (0.428) | (0.249) | (0.12) | (0.07) |
| R2 | 0.016 | 0.025 | 0.01 | 0.016 | 0.045 | 0.046 |
| Adjusted R2 | 0.011 | 0.018 | 0.005 | 0.009 | 0.041 | 0.039 |

Notes: *p<0.1; **p<0.05; ***p<0.01
Medium education and medium income used as reference categories

## Model Group 3: Travel Mode Choice Models

Table 5 summarizes the results of four model specifications. Model 1 is a baseline mixed logit model referenced against walking, which takes into account attributes of the choice alternatives, socioeconomic characteristics of the individuals, panel structure, and correlation across alternative modes. Panel 1 shows the risk preference parameters and Panel 2 shows the coefficients of the travel costs, travel time, and waiting time. In addition to the variables listed in Panels 1 and 2, Model 1 (an all subsequent models) also included four sociodemographic variables—gender, income, education, and age)—each of which was coded into several levels and interacted with the five alternatives. Furthermore, the model incorporated Gaussian random error terms in the mixed logit model. However, for simplicity, the alternative-specific coefficients for sociodemographic variables and the correlation coefficients across alternatives are not given in Table 1.

Models 2, 3, and 4 are all extensions of Model 1 that contain different sets of risk preference parameters. Model 2 incorporates only the economic risk parameters $\alpha$ and $\beta$. Model 3 incorporates only the psychometric risk parameter $\gamma$. Model 4 incorporates both the economic risk parameters $\alpha$ and $\beta$ and the psychometric risk preference $\gamma$. The subsequent discussion will elaborate on model selection first and then interpret coefficients. Overall, Models 1-4 collectively show that risk preference is clearly associated with mode choice, particularly the choice of AVs; that the economic and psychometric measures of risk preferences differ in their impacts and are largely independent of each other; and that the economic risk preference measures contributes more to the explanatory power of the model than the psychometric measure (based on likelihood ratio tests across models).

**Table 5 Choice model results**

| | **Model 1 (Baseline Model)** | **Model 2 (Econ Risk)** | **Model 3 (Psy Risk)** | **Model 4 (Econ and Psy Risk)** |
|---|---|---|---|---|
| Panel 1: travel cost variables | | | | |
| Alpha:AV | | -0.260*** | | -0.250*** |
| | | (.071) | | (.071) |
| Alpha:Bus | | -0.176*** | | -0.177*** |

| | | | | |
|---|---|---|---|---|
| | | (.051) | | (.052) |
| Alpha:Drive | | (0.021) | | -0.025 |
| | | (.068) | | (.068) |
| Alpha:RideSharing | | -0.339*** | | -0.330*** |
| | | (.062) | | (.062) |
| Beta:AV | | 0.113*** | | 0.110*** |
| | | (.028) | | (.028) |
| Beta:Bus | | 0.055** | | 0.058** |
| | | (.024) | | (.024) |
| Beta:Drive | | 0.098*** | | 0.099*** |
| | | (.022) | | (.022) |
| Beta:RideSharing | | 0.103*** | | 0.100*** |
| | | (.026) | | (.027) |
| Gamma:AV | | | 0.167* | 0.145 |
| | | | (.094) | (.095) |
| Gamma:Bus | | | -0.013 | -0.025 |
| | | | (.068) | (.068) |
| Gamma:Drive | | | 0.254*** | 0.225** |
| | | | (.09) | (.09) |
| Gamma:RideSharing | | | 0.196** | 0.178** |
| | | | (.083) | (.083) |
| Panel 2: travel cost variables | | | | |
| ASC_Bus | 0.229 | 0.322* | 0.230 | 0.361* |
| | (.183) | (.193) | (.183) | (.193) |
| ASC_RideSharing | -2.210*** | -1.900*** | -2.188*** | -1.922*** |
| | (.209) | (.223) | (.209) | (.224) |
| ASC_AV | -1.502*** | -1.340*** | -1.483*** | -1.354*** |
| | (.236) | (.255) | (.237) | (.256) |
| ASC_Drive | -0.953*** | -0.990*** | -0.910*** | -1.014*** |
| | (.243) | (.257) | (.244) | (.26) |
| WalkTime_Walk | -0.120*** | -0.119*** | -0.120*** | -0.120*** |
| | (.003) | (.003) | (.003) | (.003) |
| Cost_AV | -0.197*** | -0.197*** | -0.197*** | -0.198*** |
| | (.008) | (.008) | (.008) | (.008) |
| WaitTime_AV | -0.042*** | -0.041*** | -0.042*** | -0.041*** |
| | (.013) | (.013) | (.013) | (.013) |
| Ivt_AV | -0.089*** | -0.089*** | -0.089*** | -0.089*** |
| | (.006) | (.006) | (.006) | (.006) |
| Cost_Bus | -0.534*** | -0.527*** | -0.535*** | -0.535*** |
| | (.037) | (.037) | (.037) | (.037) |
| WaitTime_Bus | -0.078*** | -0.075*** | -0.079*** | -0.079*** |
| | (.01) | (.01) | (.01) | (.01) |
| WalkTime_Bus | -0.084*** | -0.084*** | -0.085*** | -0.084*** |
| | (.005) | (.005) | (.005) | (.005) |
| Ivt_Bus | -0.042*** | -0.041*** | -0.042*** | -0.041*** |
| | (.002) | (.002) | (.002) | (.002) |
| Cost_RideSharing | -0.167*** | -0.167*** | -0.167*** | -0.167*** |
| | (.008) | (.008) | (.008) | (.008) |
| WaitTime_RideSharing | -0.063*** | -0.065*** | -0.063*** | -0.064*** |
| | (.014) | (.014) | (.014) | (.014) |
| Ivt_RideSharing | -0.059*** | -0.060*** | -0.059*** | -0.060*** |
| | (.006) | (.006) | (.006) | (.006) |
| WalkTime_Drive | -0.070*** | -0.089*** | -0.072*** | -0.070*** |
| | (.017) | (.017) | (.017) | (.017) |
| Cost_Drive | -0.166*** | -0.166*** | -0.166*** | -0.167*** |
| | (.007) | (.007) | (.007) | (.007) |
| Ivt_Drive | -0.102*** | -0.104*** | -0.102*** | -0.103*** |
| | (.007) | (.007) | (.007) | (.007) |
| Log Likelihood | -6,014.41 | -6,001.85 | -6,011.95 | -5,999.97 |

Note: * sig < .05; ** sig < .01; *** sig < .001;

For simplicity, coefficients of socioeconomic variables and random error terms are not included in this table.

The comparison of Models 1 and 2 shows that including the economic risk parameters $\alpha$ and $\beta$ dramatically improves the explanatory power of the mode choice model compared to the baseline. A likelihood ratio test comparing Models 1 and 2 rejects the restricted model (Model 1) at a 1% significance level. The coefficients of all four alternative-specific $\beta$ parameters are significant and positive, suggesting that people with positive curvature to their value functions are more likely to choose the other four travel modes over walking. The alternative-specific $\alpha$ parameters vary much more by travel mode.

The comparison of Models 1 and 3 shows that psychometric risk preference parameter $\gamma$ also helps to predict travel mode choice. The alternative-specific coefficients of the parameter $\gamma$ are significant and positive for all modes relative to walking, indicating that psychometrically risk-seeking people are more likely to choose AVs, driving, buses, or ridesharing. By comparing the log-likelihood scores of Models 2 and 3, economic risk parameters could improve model prediction more effectively than psychometric risk parameters. Model 4 combines both the economic and psychometric measures of risk preferences, and the coefficients of the three risk preference parameters largely remain unchanged, suggesting that the economic and psychometric risk parameters independently contribute to mode choice. This is consistent with the prior finding that the economic and psychometric risk preferences are minimally correlated (see Table 3).

The next focus is the impact of $\alpha$, $\beta$, and $\gamma$ on AVs *relative* to the four other travel modes, as shown in Table 6. Overall, both economic and psychometric risk parameters contribute to the prediction of AV adoption. The interpretation of the coefficients of $\beta$ and $\gamma$ is intuitive: early adopters of AVs are likely to be those who have a larger value function based risk preference parameter ($\beta$) and a higher psychometric risk parameter ($\gamma$). In contrast, the interpretation of the probability weighting risk parameter ($\alpha$) is unclear and requires further analysis.

The $\beta$ coefficient associated with AVs is positive relative to walking and buses; however, it is insignificant relative to driving and ridesharing, suggesting that people with a larger value function based risk preference parameter are more likely to adopt AVs, which is consistent with theoretical prediction. When people on average hold a positive view about AVs, a larger $\beta$ implies that people value these positive attributes more, leading to more AV use. Geometrically, in the positive domain of x, a more convex value function $v()$ associated with a larger $\beta$ increases the value of the utility function, as shown in Figure 2 in the Appendix.

The coefficient of $\gamma$ for AVs is positive relative to walking and buses; however, it is negative relative to driving and ridesharing. This implies that risk-seeking people (measured by the psychometric method) are more likely to adopt AVs with respect to walking and buses, while less likely to adopt AVs relative to driving and ridesharing. Comparing the AV coefficients for $\beta$ and $\gamma$, we find that they are both positive relative to walking and buses, indicating consistent impacts of economic and psychometric risk preference measures for AVs relative to these modes. However, the adoption of AVs relative to driving and ridesharing is different when measured by $\beta$ and $\gamma$. This is likely due to the fact that $\beta$ and $\gamma$ represent different aspects of risk preference. The risk preference of $\beta$ is reflected in the curvature of the value function, while $\gamma$ is more a self-stated personality measure. Those with a psychometric risk-seeking personality could still prefer driving to AVs. For example, one study by the UK Automobile Association found that 65% of people liked driving themselves; hence, they were less willing to switch to AVs (Maynard et al., 2014). This contrast between $\beta$ and $\gamma$ may reflect a broad difference of risk preference parameters between economics and psychology. Given that choice models are utility-based and economic risk preference based on PT can be more directly tied to a utility interpretation that psychometric measures, we might trust them more in this application. However, it is an important area for future research to understand the connection and difference between economic and psychological measures of risk preferences.

**Table 6 Summary of $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$ impacts on adoption of AVs relative to other modes (based on model 4)**

| | | |
|---|---|---|
| $\boldsymbol{\alpha}$ | **Effect on AV** | |
| | Relative to Walking | Negative |
| | Relative to Bus | Insignificant |
| | Relative to Driving | Negative |
| | Relative to Ridesharing | Positive |
| $\boldsymbol{\beta}$ | **Effect on AV** | |
| | Relative to Walking | Positive |
| | Relative to Bus | Positive |
| | Relative to Driving | Insignificant |
| | Relative to Ridesharing | Insignificant |
| $\boldsymbol{\gamma}$ | **Effect on AV** | |
| | Relative to Walking | Positive[6] |
| | Relative to Bus | Positive |
| | Relative to Driving | Negative |
| | Relative to Ridesharing | Negative |

The interpretation of the probability weighting risk parameter ($\alpha$) for AVs is less clear. The effect is negative relative to walking and driving, and positive relative to ridesharing. $\alpha$ influences decisions under risk for the events with very small or very large probabilities. Hence, those risky dimensions of AV with small probabilities, though large gains or losses, could be associated with $\alpha$. Consider safety as an example. When $\alpha$ becomes smaller, people tend to overestimate small probabilities of safety problems involved in AVs, leading to larger disutility and less adoption of AVs. However, a good explanation why the effect of $\alpha$ is negative relative to walking and driving seems unclear. As mentioned in the introduction, this study did not measure the specific dimensions or sources of risk associated with AVs, such as accidents, time reliability, and travel costs; thus, this study alone cannot pinpoint which risk dimension of AVs have small probabilities and large gains or losses. The above example of AV safety only illustrates the potential ways that $\alpha$ could be interpreted.

[6] Model 4 and Model 5 are different in the significance level of this coefficient. Overall the p-value is at the boundary of marginal significance (10% level), and the value of this coefficient is always positive.

Note that the median value of $\alpha$ shown in Model Group 1 is 0.88, smaller than the normative social optimum $\alpha = 1$; the median value of $\beta$ is 0.91, also smaller than the normative social optimum $\beta = 1$. These values imply that people tend to use AVs less than the social optimum, either owing to concerns (such as safety or liability) or their concave value function.

## Limitations

Some weaknesses remain in this research. First is the distinction between risk and uncertainty; the focus of this paper is the impact of risk preference rather than uncertainty preference. While risk aversion is one specific type of uncertainty aversion, uncertainty aversion is also relevant given that the exact probabilities of an AV service and its technology are difficult to measure. This study operationalized prospect-theory-based risk preference; however, it did not design a more detailed survey to measure the probabilities of AV-related risky dimensions. Therefore, it did not have the opportunity to distinguish between the gain and loss domains of AVs. To combine generic risk preference parameters and specific risk dimensions of AVs is an important future research area.

Regarding case selection, Singapore cannot be representative of countries or cities worldwide; hence, the external validity of this study is yet to be evidenced. Regarding measurements, the economic risk parameters were derived using only four indifferent pairs for each individual, and the psychometric risk parameter was derived using only three responses from Likert-scale statements. The small number of questions was decided on to reduce the burden on survey respondents, but having additional questions could make measurements of both economic and psychometric risk preferences more accurate.

Regarding modeling, the three model groups were estimated separately and sequentially. Given the large number of regressions in Model Group 1 needed to derive the economic risk preferences, it was computationally intractable to simultaneously estimate these parameters with Model Groups 2 and 3. Furthermore, the mode choice models in Model Group 3 use only linear utility functions rather than more complex model specifications. While the model specification could be further enriched, for example by including interaction terms between the risk preference parameters and all other variables, this would dramatically increase the number of coefficients and make coefficient interpretation much more difficult. Future work could include the 3 parameters $(\alpha, \beta, \gamma)$ * 5 modes * number of uncertain attributes (time, cost, safety, reliability, comfort, convenience, etc.) * 2 (gains vs. losses), but such a comprehensive analysis is beyond the scope of this study.

## DISCUSSION

This study analyzes the relationship between risk preference and the adoption of AVs, and answers three questions: (1) how to measure risk preference using psychometric methods and economic techniques based on prospect theory (PT); (2) how risk preference parameters are associated with socioeconomic variables; and (3) how risk preference parameters are associated with the adoption of AVs. The research was motivated by the importance of AVs and risk preference, as well as their intuitively strong connection. The research derived the economic and psychometric risk preference parameters and incorporated them into regressions and mode choice models based on a large-scale SP survey conducted in Singapore with 1,142 valid observations.

The three research questions correspond to three model groups. In Model Group 1, this study found that economic risk preference parameters estimated from our survey are consistent with theoretical predictions. The median values of α and β are both less than one, implying that people tend to overestimate small probabilities and are overall risk-averse. In Model Group 2, this study found that young, high-income, fully-employed individuals with higher education are the most risk-seeking social group, while older and lower-income individuals are more risk-averse in the adoption of new technology with overall benefits but small probability of large losses. Model Group 3 shows a significant association between risk preference parameters, measured by both economic and psychometric methods, and the choice of AVs, even after controlling for the panel structure of the data, individual socioeconomics, attributes of the travel alternatives, and correlations among alternatives. The two economic risk preference parameters and the one psychometric risk parameter are mutually independent; and all contribute to predicting AV use. Economic risk parameters contribute more than the psychometric parameter in terms of model explanatory power. The early adopters of AVs are likely to be those who have a larger value function based risk preference parameter ($\beta$) and higher psychometric risk parameter ($\gamma$). On the other hand, the interpretation of ($\alpha$) is unclear because it might depend on the exact dimension or source of AV-related risk in question, a level of detail beyond the scope of this study.

The combined results from the three model groups suggest policy interventions at both aggregate and disaggregate levels from the perspective of behavioral welfare economics. At the aggregate level, people misperceive probabilities and are overall risk-averse. This leads them to under consume AVs relative to the social optimum benchmark represented by the expected utility models. This problem is similar to the problem of underinvesting in vehicle fuel economy (Greene et al., 2008). This collective under-consumption could give grounds for government actions to encourage AV adoption, such as investment in AV-related infrastructure, integrating AV technology in public transit, and better informing the public about the technology. At the disaggregate level, the elderly, poor, and females are particularly susceptible to overestimating small probabilities of losses in AVs, and thus are less likely to adopt AVs. However, one important equity and efficiency benefit of AVs is precisely its mobility enhancement for the risk-averse elderly, disabled, and other marginalized people. To deal with this dilemma, government can take actions to facilitate the usage of AV among these social groups. Possible policies could be price discounts or subsidies offered to socially marginalized groups to encourage their AV usage, although some caution still remains due to uncertainty in the long-term effects of AVs. In general, the government needs to design and implement regulations, safety standards, and liabilities of AVs, and these are fundamentally about risk allocation. Beyond these specific policy suggestions, AV risk preference is relevant to a large number of stakeholders. For example, the individualized risk preference parameters estimated here might help insurance companies design coverage packages that allocate the risks of AVs because larger risk aversion parameters often imply more profit margin for insurance companies.

This paper calls for further studies related to AVs, risk, and mode choice models. One such line of future research could be to expand risk preferences to operational and policy analyses of AVs. For example, future studies can analyze how transportation planners, engineers, and policymakers perceive AV-related risk, and how their risk preferences influence AV-related system design or AV promotion policies. Additionally, it would be interesting to continue analyzing the multiple dimensions of risk preference in the context of AVs. While this study has provided some preliminary insights by differentiating the economic and psychometric measures of risk preferences, it would be important to examine the behavioral mechanisms of how different types of risk preference influence the multiple risky aspects of AV use. By using individualized risk preference parameters, such as those developed in this study, researchers could potentially reframe the predominantly expected utility-based choice models to PT-based choice models. Overall, because AVs will substantially impact the future of transportation systems, and uncertainty is nearly inevitable in any choice situation that involves this emerging technology, the association between AVs and risk is a fertile area for future research.

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## APPENDIX I INTERPRETATION AND ESTIMATION OF ECONOMIC RISK PREFERENCE PARAMETERS

As shown in Figure 2, the parameter $\alpha$ portrays the curvature of the probability weighting function, and $\beta$ describes the curvature of the utility function. As recommended, Figure 2 uses the power form of the value function and Prelec form of the probability weighting function following Equation 2 in the main text (Dhami, 2016). The two functions with the three values (0.5, 1, and 2) of $\alpha$ and $\beta$ were plotted in the upper panel of Figure 2. Theoretically, the $\alpha$ and $\beta$ values of a typical individual are between zero and one. More precisely, PT indicates that people overestimate very small probabilities and underestimate very large probabilities, as shown by the S-shaped red curve in the left graph of the upper panel. Economic theories also indicate that people have concave value functions, as shown by the concave red curve in the right graph of the upper panel. However, it is quite likely that individuals have heterogeneous probability weighting functions and utility functions; thus, the two parameters could exceed one, depending on specific individuals (De Palma et al., 2008). When $\alpha$ equals one, the perceived probabilities are the same as the actual probabilities, reducing the utility functions based on PT to the expected utility functions. When $\beta$ equals one, the value function reduces to a straight line extending from (0, 0) to (1, 1). When $\alpha$ and $\beta$ are closer to infinity, the shapes of the two functions are more similar to the blue curves plotted in the upper panel.

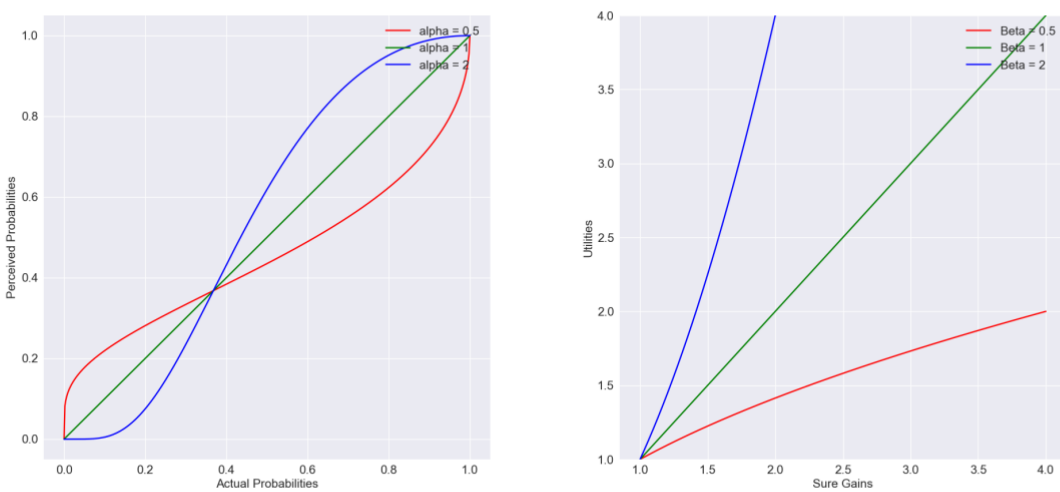


Figure 2a Theoretical demonstration

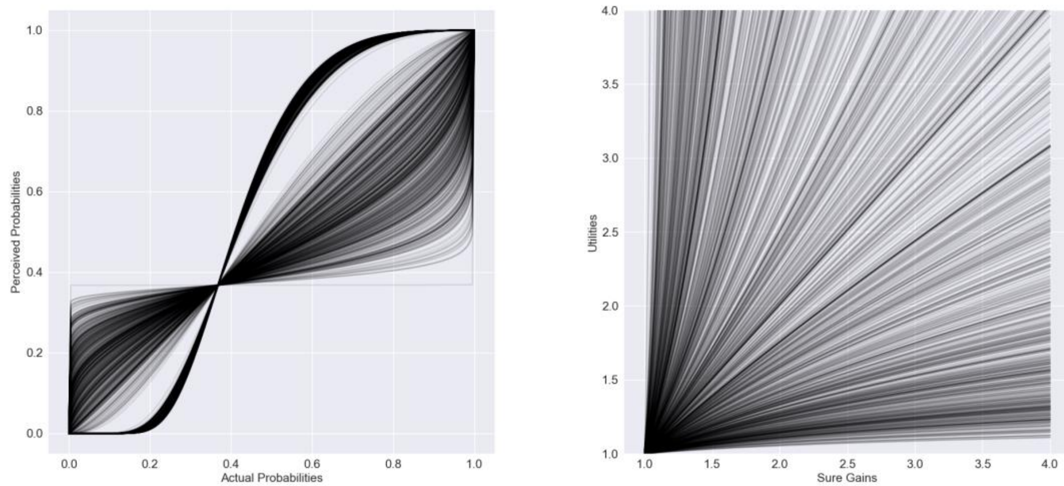


Figure 2b Estimated values from respondents

**Figure 2 Probability weighting functions and value functions**

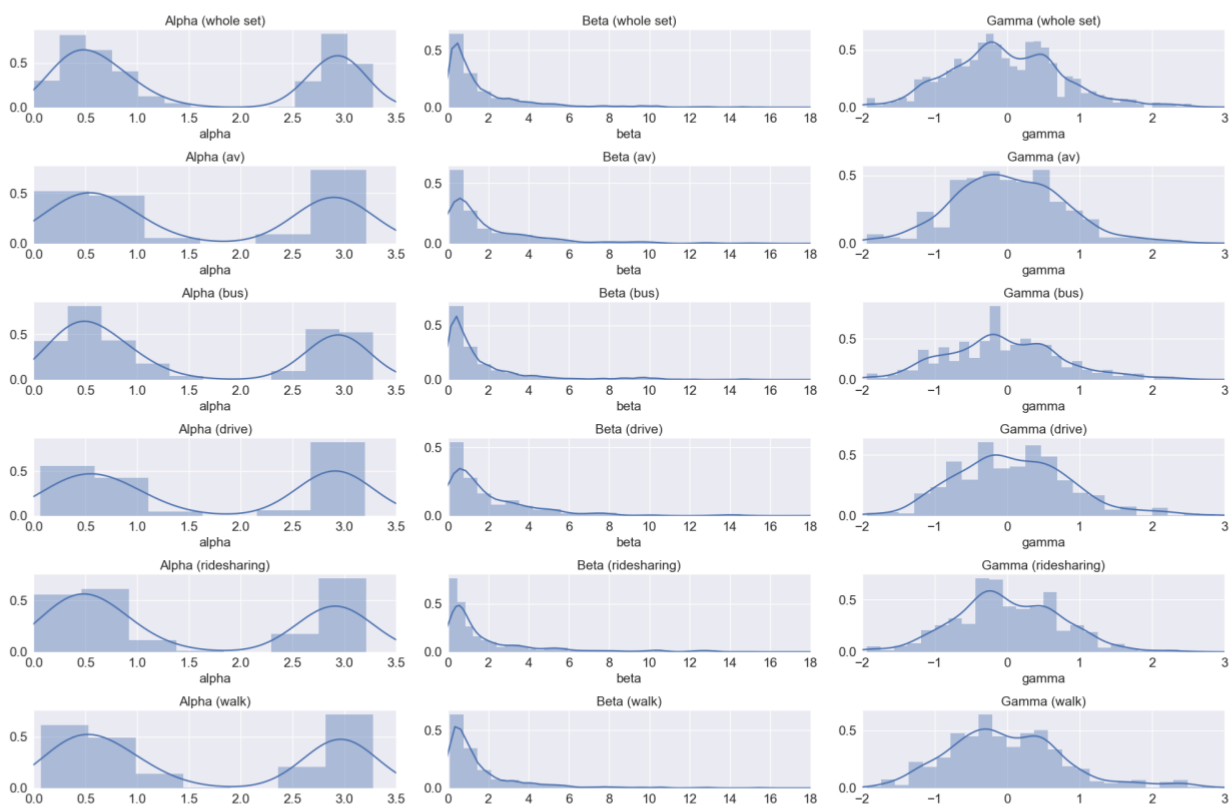


**Figure 3 Histograms of alpha, beta, and gamma; row 1: distribution of the whole dataset; row 2-6: distribution for each choice**

A critical difference between $\alpha$ and $\beta$ is that parameter $\alpha$ pertains to extreme-range (very small or very large) probabilities, while parameter $\beta$ is related to the overall risk preference, and particularly the middle-range probabilities. This is because the S-shaped probability weighting function distorts the actual probability the most at the extreme-range probabilities, and less when the actual probabilities are in the middle range. Owing to this distinction, the two parameters are connected to different types of risky behavior. For example, the events with extremely low probabilities may include terrorism attacks, winning at gambling, or car accidents. A person with a smaller $\alpha$ tends to overestimate the small winning rate of gambling more, and thus, is more likely to be attracted to it. The events with moderate probabilities could be many daily events. A person with a larger $\beta$ tends to be risk seeking overall, and a person with a smaller $\beta$ tends to be risk averse when it comes to these daily events. Consider driving as an example. If driving has a moderate probability of evoking some exciting experiences, then a person with a larger $\beta$ tends to drive more. The bottom panel of Figure 2 and Figure 3 visualize $\alpha_i$, $\beta_i$, and $\gamma_i$ estimated in our study. Both figures show the large heterogeneity of risk preference across the five travel alternatives included in the SP survey.