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Investigating the effectiveness of COVID-19 pandemic countermeasures on the use of public transport: A case study of The Netherlands

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ABSTRACT

During the COVID-19 pandemic, public transport in many cities faces dramatic reduction of passenger demand. Various countermeasures such as social distancing and in-vehicle disinfection have been implemented to reduce the potential risks concerning infection, the effectiveness in promoting the use of public transport however remains unclear. Unlike the usual situation where time and cost are the main factors affecting travel decisions, the uncertainty hiding behind the behavior change of public transport users in a pandemic might be greatly affected by the control measures and the perception of people. This paper therefore aims to examine the effects of COVID-19 related countermeasures implemented in public transport on individuals' travel decisions. We explore the extent to which do policy countermeasures influence different groups of people on the use of public transport. An error component latent class choice model was estimated using the data collected in the Netherlands. Results show that the restrictions policy lifted by the Dutch central government have significant effect on individuals' transportation mode choice decision during the pandemic. The related measures adopted by the public transport sector, by contrast, present different effects on different people. The older and highly educated people are more susceptible to enforcement measures, whereas young and single Dutch citizens are more accessible to non-compulsory measures. Moreover, compared with other private modes, public transport is generally identified as a riskier option, and the average willingness to travel descends. Findings of this study are helpful for the authorities in designing and promoting effective policies in the context of pandemics.

1. Introduction

Environmental problems and global climate changes are among the greatest challenges in the 21st century. Based on the data from European statistics, 47% of CO₂, 42% of NOₓ, and 18.4% PM emissions are resulted from on-road transportation and most of the emissions are emitted by private cars (Sun et al., 2018). There is a consensus that making more use of public transport services can be advantageous for reducing emissions and tackling climate change. Therefore, many cities and countries worldwide are in the process of enhancing their public transport systems with new technologies and cleaner fuels. In the meantime, various novel transportation services (e.g., car-sharing, ridesharing, and bike-sharing services) have also been developed. Because of the potential to reduce the number of people driving single-occupancy vehicles, these services are granted a specific role to improve energy efficiency and have a positive environmental impact. This also explains why both researchers and practitioners put much effort into designing and optimizing these services.

However, all of that changed with the outbreak of COVID-19. As a response to the pandemic and protective measures adopted by governments, residents in different countries were all forced to change their daily travel patterns (Beckans Hensher, 2020; Oum and Wang, 2020; Eisenmann et al., 2021). Many prior efforts exploring the effects of COVID-19 on travel behavior showed that trips decreased significantly in early outbreaks. The uses of shared modes of transport, such as public transport and shared mobilities, are also found to have a noticeable drop (Gibbs et al., 2020; Chan et al., 2020; Barbieri et al., 2021). Just like the shared houses provided by Airbnb and Booking are not that attractive during the pandemic, public transport options, which are traditionally promoted as green travel alternatives, also have a different position due to the fear of virus transmission in shared spaces. Even more to the point, individual-based shared mobilities (e.g., shared car, bike, and E-scooter) are not sharing space with other users but just sharing the use. Because of the characteristic of shareability, the intention to use these

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individual-based shared mobilities is also shrunk. As a result, many car-free households project a willingness to acquire personal vehicles to avoid using shared modes. The resulting consequence of the mounting personal vehicles is the more severe traffic congestion in a long term.

In addition to the perceived risk, policies of government restriction and COVID-19 countermeasures adopted by public transport operators are the determinants of travel choices. Recent research has investigated the changes in travel patterns and activities during the pandemic (Gibbs et al., 2020; Shamshiripour et al., 2020; Eisenmann et al., 2021; Barbieri et al., 2021; Luan et al., 2021), however, the reason and patterns on how people adapted their travel behavior are not explored sufficiently. Also due to the unheard of this special situation, little is known about the differences in travel behavior between different user groups. The decision-making mechanism underlying the difference and how policy should be designed to promote the use of public transport need to be better understood.

To shed light on these essential aspects for policymaking, we carried out a stated choice experiment in the context of the Netherlands. The choice of the experiment method was because no unified data exists with respect to a specific “stage” of policies. Relying on these hypothetical choice situations, we aim to answer the following research questions: (1) How does travel behavior change under the pandemic with the consideration of COVID-19 related policies? (2) Are there any differences in the acceptance of COVID-19 related policies between different segments of the population? (3) Can these COVID-19 policy interventions redeem risk concerns of public transport?

While this study is confined to a specific country (i.e., The Netherlands), we must admit that there are certain differences among different countries in culture, economic development, and COVID-19 countermeasures adopted by the governments (Chorus et al., 2020). However, we could also observe that the COVID-19 countermeasures implemented by some western governments (e.g., Britain and Germany) are indeed consistent with those held in The Netherlands (Eisenmann et al., 2021). Therefore, in this case (i.e., similarities exist between countries in terms of the social tension between COVID-19 countermeasures and travel demand), we expect our results to hold lessons well for other countries beyond the Dutch context.

The remainder of the study is structured as follows. Section 2 gives an overview of related literature on COVID-19 and mobility behaviors. Section 3 presents the experimental design used in this paper and discusses the procedure of data collection, followed by developing an error component latent class choice model in Section 4. Estimation results and major findings are then elaborated in Section 5. Section 6 discusses the related policy implications and recommendations that can be obtained from our study. Lastly, the paper is concluded with some discussions and summaries some future research directions.

### 2. Literature review

The COVID-19 pandemic has a massive influence on people’s daily lives. This impact is not only on life safety but also on lifestyle. Indeed, several epidemics resulting from viruses (such as SAS, H1N1, and MERS) existed before the COVID-19 pandemic, and the early pandemics have afforded us some valuable lessons (Wen et al., 2005; Fenichel et al., 2013; Kim et al., 2017). These previous empirical studies have suggested that people view reducing the use of public transport as a safeguard to free from infection. Some COVID-19 related studies also indicated a significant mode shift from public transport to private modes (e.g., bikes and cars) (Bucsky, 2020; Eisenmann et al., 2021). A sample of recent studies on these behavioral changes because of the COVID-19 pandemic is summarized in Table 1.

By summarizing the recent studies, it can be found that a dominant number of studies exploring the effects of the COVID-19 pandemic on travel behavior reveal that the willingness to travel has remarkably declined in the pandemic. Of all transport modes, it was public transport on which the COVID-19 had the most direct effect (Bucsky, 2020; Eisenmann et al., 2021; Zhang et al., 2021; Zhang et al., 2021). Some scholars also found that if COVID-19 is under control and public transport safety and hygiene can be guaranteed, people are still willing to travel outside (Beck and Hensher, 2020; Bracarense and de Oliveira, 2021). There is no denying that the existing studies regarding COVID-19 and travel behavior offered valuable insights into behavior changes in the pandemic. However, much research exists only on aggregate statistics. The detailed analysis of traveler’s choice behavior and the authentic effects of COVID-19 countermeasures on reducing the potential risk perception in public transport is largely missing.

So far as we know, only a few studies conducted the individual choice analysis under the COVID-19 pandemic and public transport. Based on both the revealed and stated choice data collected in Italy, Scorrano and Danielis (2021) investigated the mode choice behavior before and during the COVID-19 pandemic. In their model, the impact of the pandemic on mode choice is parametrized as a mode-specific

| Reference | Study time | Study area | Data source | Findings |
|-----------|------------|------------|-------------|----------|
| Bucsky (2020) | March 2020 | Budapest, Hungary | Historical data from multiple sources | 1. The aggregated travel demand decreased nearly half. 2. Because of COVID-19 measures, modal share of public transport decreased dramatically. 3. Car and bicycle usages both have a great growth. |
| Eisenmann et al. (2021) | April 2020 | Germany | Online travel survey | 1. Public transport was hit hardest. 2. Private modes, especially the private car, became more important. 3. Heterogeneity exists between individual changes in transport mode usage. |
| Zhang et al. (2021) | April-May 2020 | No specific area | A worldwide expert survey | 1. More shifts of activity participation from physical spaces to virtual spaces. 2. Significant modal shifts away from public transport usage. 3. In the long term, car dependence may increase. |
| Zhang and Fricker (2021) | January-May 2020 | The United States | Historical non-motorized transportation modes data | 1. There was heterogeneity in the impacts of COVID-19 on daily non-motorized activities. 2. The non-motorized activities decreased in densely populated cities. 3. Walking and bicycle activities, by contrast, increased in less densely populated cities. |
| Bracarense et al. (2021) | April-May 2020 | Brazilian cities | A web-based survey | 1. The behavior regarding essential activities in the pandemic depend on pre-pandemic travel patterns and socioeconomic factors. 2. There are not many opportunities for public transport users to switch from routine to purchasing. 3. Post-pandemic intention is statistically dependent on activities' characteristics. |
coefficient and found to negatively influence the use of public transport. Specifically focusing on public transport, Cho and Park (2021) used a stated preference survey collected in Seoul to investigate the behavioral differences characterized by the mode-specific crowding multiplier. They found that the crowding impediments after the outbreak of COVID-19 are higher than before the pandemic, confirming the conjecture that passengers are sensitive to the crowed in public transport. Luan et al. (2021) also used a stated choice experiment to investigate the impact of COVID-19 on travel mode choice behavior in China. Several conventional public transport attributes (e.g., travel time, travel cost, waiting time, and congestion degree) were considered in their experiment. In contrast, the specific changes in attributes relevant to the COVID-19 were not addressed.

What calls for special attention here is that those studies primarily focus on the effects of COVID-19 itself, e.g., compare the travel behavior before and after the outbreak of COVID-19 directly. The reasons behind behavioral changes in the pandemic and the impact of different pandemic stages are, in contrast, not assessed. In addition, because of the differences in economic development level, culture, and severity of the epidemic, the lessons learned from one country cannot be extended to other countries. Our study takes the Netherlands as an example, and the study time is selected during a particularly restricted period of lockdown in The Netherlands. What makes our study unique is that it is the first study, to the best of our knowledge, that uses choice experiments to investigate the main drivers underlying the travel behavior changes that were imposed in the wake of the COVID-19 crisis. Furthermore, preference heterogeneity between people were identified with respect to the different groups of people. The findings of this study would offer the government useful insights on developing policy measures, especially when having targeted groups.

3. Survey and experimental design

To investigate the transportation mode choice behavior and the taste variation in traveling of shared spaces and vehicles under COVID-19 pandemic countermeasures, we designed a Web-based survey, in which a stated choice experiment was included. The stated choice experiment could entitle researchers to control over the variation of attributes and attribute levels and can appropriately recognize the relative importance of respondents assign to each influencing attribute (Guo et al., 2020; Chorus et al., 2020).

Without expressing a particular cause-and-effect, we conveyed to respondents that, with the changes in the severity of the COVID-19 pandemic, the central government and related authorities might strengthen or lift the current measures. They were taught that we were intrigued with, under such scenes, whether they would change their travel preferences. By realizing the related backgrounds before the formal experiment, respondents could take these factors into account when making a choice. In this experiment, five transportation modes (i.e., car, bus, bike, shared E-bike, and walk) were presented to respondents. In addition, an extra option “not travel” was also included.

3.1. Experimental design

The attributes considered in the stated choice experiment were mainly derived from relevant studies and based on the real situation. The examination of the relevant literature suggests that travel contexts are critical influencing factors in choice decisions (e.g., Swait et al., 2002; Kim et al., 2017). Therefore, in this paper, two four-level attributes and one two-level attribute were considered to represent the travel context. These attributes include COVID-19 restrictions policy, travel distance, and travel purpose. The context attribute of the COVID-19 policy was defined by a four-level COVID-19 alert system adopted in reality by the Dutch government. In reality, different rules were implemented with respect to each level of the alert system, restricting and influencing people’s travel behavior. A detailed introduction of the alert system was also provided before the official stated choice experiment to help interviewees better imagine the authentic situation. What needs to be pointed out is that this context attribute could implicitly consider different severity levels of the pandemic.

In addition, two travel distance scenarios are designed considering urban sizes and feasible walking/cycling distance, whereas 2.5 km and 5 km were used to represent a short-haul trip and a long-haul trip, respectively. Note that the 5-km distance indeed represents a half of the length of medium size Dutch cities and was commonly used by many previous studies (Molin and Timmermans, 2010; Arentze and Molin, 2013; van den Berg et al., 2018). Moreover, the Dutch statistics show 2.5 km is the maximum walking distance that Dutch residents could accept in normal life, and almost all bicycle trips in The Netherlands are shorter than 5 km. Furthermore, the origins and destinations in the experiment can be floated. It is, if the respondents like, the origin and destination of the intended trip could be any arbitrary locations as long as the total distance is limited within 2.5 or 5 km.

Apart from the travel contexts, the alternative-specific attributes are also highly relevant to influence transportation mode choice behavior (Guo et al., 2020). Based on the existing literature, transportation modes were usually defined in terms of travel costs, travel time, out-of-vehicle time, congestion time, and having seats or not. However, due to the pandemic, traffic congestion has been greatly alleviated in the last year (Arellana et al., 2020). The data collected by the road authority also confirm the finding that traffic congestion had a significant reduction. Moreover, because of the measures adopted by the public transport operators (e.g., 1.5-m social distance rule), finding a seat on buses is also not an issue nowadays. Thus, the alternative-specific attributes selected in this paper only include three attributes: travel time, out-of-vehicle time, and travel cost. The levels of these attributes were determined with respect to the actual traveling situation (from Google Map and related calculator websites).

In the case of public transport, few studies are conducted for the levels of factors, which are elaborated with COVID-19 related measures. As discussed early, some restrictions and measures have been adopted in the Dutch public transport sector. These measures could be summarized into five main categories: onboard passengers’ limitation, requirement on facemask, reinforcing disinfection, 1.5-m social distance rule, and offering hand rubs. To investigate the impacts of these measures, we attached the five regulation-related attributes to the bus option. Regarding the allowed number of passengers, we consider the possible choices adopted by the public transport sector, setting 25% of the total number of seats that could be occupied as the lowest level of passenger number. Therefore, four levels of the attribute are defined, 100%, 75%, 50%, and 25% of the total number of seats that could be occupied. Moreover, the requirement on facemask, 1.5-m social distance rule, and the offer of hand rubs all varied in two levels. Level 1 represents the existence of the measure, while level 2 indicates there is no specific regulation. The disinfection frequency is another important measure for the public transport sector based on real experience. Therefore, the disinfection frequency was also included in this study and varied from a low infection frequency to a high frequency. Table 2 presents a detailed list of attributes and their levels.

The experiment, in total, has thirteen four-level attributes and four two-level attributes, leading to \(4^{13} \times 2^4\) choice tasks for a full factorial design. Given that the full factorial design is indeed impossible to implement and is overwhelming for respondents to complete, only a fraction of the profiles (i.e., the fractional factorial designs) should be used instead. In this study, the experiment was designed to ensure that all attributes are statistically independent. More specifically, we created an orthogonal fractional factorial design using SAS, consisting of 64 choice tasks. The 64 choice tasks were then grouped into eight blocks such that each respondent answers eight choice tasks after agreeing to take the survey. For more details of the design principle, interested readers could refer to Hensher et al. (2005). A sample choice task presented to respondents is shown in Fig. 1. Taking car as an example, the
alternative is represented by the level 3 of the attribute Travel cost and level 1 of the attribute Travel time.

3.2. Data analysis

The data were collected in The Netherlands from 15th December 2020 to mid-January 2021. This time also lies in the hard lockdown period of The Netherlands. The survey was implemented using an online survey, Qualtrics. Answering the entire questionnaire needs to take about 10–15 min. To cover the respondents who have limited access to the internet and are also inactive in participating in online surveys, this study recruited respondents from both web and face-to-face interviews. As is well known, because of the COVID-19 policies, it is not easy to collect the data in face-to-face interviews. Instead, we recruited some volunteers to collect the questionnaire from their family members (especially seniors) on a face-to-face basis. The other part of respondents was recruited through social media, Facebook, by using posts and messages. That is because social media, which could connect different groups of people, has been used more frequently after the outbreak of COVID-19 (Ahmed et al., 2020). In addition, to limit the potential bias, a random sample was drawn. Several controls on the characteristics of respondents were also implemented such that the sample is representative. In order to ensure the study’s scope, they were also required to live in The Netherlands. The introduction of the survey, e.g., research purposes, consent form, and contact information were offered before people participated the questionnaire. The data collection effort was approved beforehand by the Ethics Board of the Eindhoven University of Technology.

Finally, a total of 684 respondents were invited, of these, 432 completed the whole questionnaire (indicating a drop-out rate of 36.8%). A data cleaning procedure was implemented before analysis. The responses completed within 5 min were labeled as invalid observations and disregarded, and the data from respondents who presented stereotyped response patterns were also excluded. Consequently, a sample consisting of 3152 observations from 394 respondents was used for later analysis.

Table 3 summarizes the descriptive statistics of several typical socio-
demographic variables of the valid respondents. It shows that gender is almost evenly split. As for age, 17.0% of the respondents were younger than 25 years old, 65.7% were between 26 and 55 years old, and 17.3% were older than 56 years old. More than half of the respondents were single (67%), 25.6% were married but without children, and only 7.3% are parents. Moreover, 71% of the respondents have higher educational background. Similarly, 89.6% of the respondents have a job (regardless of part-time or full-time). Finally, 53.3% of the respondents belong to car-own household.

4. Model specification

In this paper, the analysis of the individuals’ travel choices is based on the random utility theory, where an individual $n$ chooses the alternative with the highest utility when facing several alternatives in a specific choice situation $s$ ($s \in S$). Thus, the utility of alternative $i$ evaluated by individual $n$ in choice situation $s$ can be mathematically defined as follows.

$$ U_{nsi} = \beta_{nsi}^{C} x_{nsi}^{C} + \beta_{nsi}^{X} x_{nsi}^{X} + \beta_{nsi}^{A} x_{nsi}^{A} + \varepsilon_{nsi} $$  \hspace{1cm} (1)

Where $x_{nsi}^{C}$ is a vector of context variables, $x_{nsi}^{X}$ is a vector of attributes regarding COVID-19 countermeasures, and $x_{nsi}^{A}$ is a vector of alternative-specific attributes. The vectors $\beta_{nsi}^{C}, \beta_{nsi}^{X},$ and $\beta_{nsi}^{A}$ are parameters to be estimated. $\varepsilon_{nsi}$ represents a random disturbance term. To reflect the possible panel effects induced by the repeated choices (i.e., the serial correlation within an individual), we define the random disturbance term $\varepsilon_{nsi}$ as follows.

$$ \varepsilon_{nsi} = \eta_{nsi} + \xi_{nsi} \delta_{nsi} \sim N(0, \sigma_{\varepsilon}), \xi_{nsi} \sim G(0, \sigma_{\xi}) $$  \hspace{1cm} (2)

where $\beta$ is the alternative-specific constant (ASC). $\eta_{nsi}$ is defined as an individual-specific error component. This term varies across individuals but keeps constant over different choice situations for a specific individual. In this paper, $\eta_{nsi}$ is assumed to follow a normal distribution with zero mean and a standard deviation of $\sigma_{\eta}$. Furthermore, the random error term, $\xi_{nsi}$, is assumed to be independently and identically (IID) Gumbel distributed with a standard deviation of $\sigma_{\xi}$. Also noteworthy, the traditional multinomial logit (MNL) model assumes that tastes (e.g., parameter vectors) are the same within the population. Nevertheless, the fact is that tastes will differ across people, also within segments. Failing to capture this unobserved taste heterogeneity may lead to an unreliable analysis. Therefore, we adopt the latent class model in this paper, where the parameters are assumed to be different in segments. Let $s_{nt}$ be the probability that individual $n$ belongs to latent class $t$, and the class membership model could be defined as follows.

$$ s_{nt} = \frac{\exp(\alpha_{nt} + \theta_{nt} Z_{nt})}{\sum_{t=1}^{T} \exp(\alpha_{nt} + \theta_{nt} Z_{nt})} \hspace{1cm} (3) $$

where $\alpha_{nt}$ represents a class-specific constant, $Z_{nt}$ is a vector of individual-specific variables, and $\theta_{nt}$ is a vector of parameters to be estimated. To identify the parameters involved Equation (3), the constant and parameter vector of the $t$th class are set as $0$. Thus, each class $t$ will have a unique parameter vector $\beta (\beta_{t} = \beta_{nt}^{C} \cup \beta_{nt}^{X} \cup \beta_{nt}^{A})$ in Equation (1), which could present the preferences of individuals assigned to the specific class.

Furthermore, one thing to note here is that a subset of the alternatives included in the choice experiment shares some common factors. For example, car, bike, and walk are individual and private modes, while bus and shared E-bike are both transportation modes with shared features. In this case, the IIA (Independence from Irrelevant Alternatives)-assumption between alternatives is violated, and assuming independent error terms (in Equation (2)) could lead to bias in parameter estimates. To take into account the correlation between alternatives that are not accounted for by the latent class model, we employ the error component latent class model. In this model, an additional error component that captures the preference heterogeneity, $v_{ns} share$, is added to the utility functions of alternatives with shared features. As a result, the utility functions of all alternatives can be specified as follows.

$$ U_{nsi, car} = \beta_{nsi}^{C} x_{nsi}^{C} + \beta_{nsi}^{X} x_{nsi}^{X} + \beta_{nsi}^{A} x_{nsi}^{A} + \varepsilon_{nsi} + v_{ns} share $$  \hspace{1cm} (4)

$$ U_{nsi, bike} = \beta_{nsi}^{C} x_{nsi}^{C} + \beta_{nsi}^{X} x_{nsi}^{X} + \beta_{nsi}^{A} x_{nsi}^{A} + \varepsilon_{nsi} $$  \hspace{1cm} (5)

$$ U_{nsi, walk} = \beta_{nsi}^{C} x_{nsi}^{C} + \beta_{nsi}^{X} x_{nsi}^{X} + \beta_{nsi}^{A} x_{nsi}^{A} + v_{ns} share + \varepsilon_{nsi} $$  \hspace{1cm} (6)

$$ U_{nsi, bus} = \beta_{nsi}^{C} x_{nsi}^{C} + \beta_{nsi}^{X} x_{nsi}^{X} + \beta_{nsi}^{A} x_{nsi}^{A} + \pi_{nsi} share + \varepsilon_{nsi} $$  \hspace{1cm} (7)

$$ U_{nsi, ESB} = \beta_{nsi}^{C} x_{nsi}^{C} + \beta_{nsi}^{X} x_{nsi}^{X} + \beta_{nsi}^{A} x_{nsi}^{A} + \pi_{nsi} share + v_{ns} share + \varepsilon_{nsi} $$  \hspace{1cm} (8)

where the error component $v_{ns} share$ is assumed to follow a normal distribution with zero mean and a standard deviation of $\sigma_{\varepsilon}$. Conditional on $v_{ns} share$ and $s_{nt}$, the choice probability takes on a logit form:

$$ P_{ni}(i|v_{ns} share, s_{nt}) = \frac{\sum_{i=1}^{T} \exp(\beta_{ni}^{C} x_{ni}^{C} + \beta_{ni}^{X} x_{ni}^{X} + \beta_{ni}^{A} x_{ni}^{A} + \delta_{ni} v_{ns} share)}{\sum_{j=1}^{T} \exp(\beta_{nj}^{C} x_{nj}^{C} + \beta_{nj}^{X} x_{nj}^{X} + \beta_{nj}^{A} x_{nj}^{A} + \delta_{nj} v_{ns} share)} $$  \hspace{1cm} (9)

where parameter $\delta_{ni}$ is a binary variable, which denotes whether the error component is included in the utility function. If the error component is included, $\delta_{ni} = 1$, otherwise $\delta_{ni} = 0$.

By integrating the conditional choice probabilities over $f(v_{ns} share|X_{ni}^{C}, X_{ni}^{X}, X_{ni}^{A})$, the unconditional choice probability of alternative $i$ for individual $n$ in choice situation $s$ could also be specified as:

$$ P_{ni} = \int f(v_{ns} share|X_{ni}^{C}, X_{ni}^{X}, X_{ni}^{A}) \cdot P_{ni}(i|v_{ns} share, s_{nt}) \cdot d(v_{ns} share) $$  \hspace{1cm} (10)

where, $f(v_{ns} share|X_{ni}^{C}, X_{ni}^{X}, X_{ni}^{A})$ is a density function of $v_{ns} share$. It should be noted that the integral involved in Equation (10) does not have a closed-form solution. Therefore, to evaluate the integral, the maximum
simulated likelihood method is employed. Instead of using exact probabilities, the maximum simulated likelihood method exploits the average results by simulating probabilities (see Train, 2009, for more details). Then, the full simulated likelihood function of the model could be defined as follows.

$$LL = \sum_{n=1}^{N} \log \frac{1}{R} \sum_{r=1}^{R} \left( \prod_{s=1}^{S} \prod_{t=1}^{T} (P_{rst})^{y_{rst}} \right)$$

(11)

where, $R$ is the number of draws from density $f(v_{ns}, |X_n, X_s, X_t, \pi, \gamma_{nst})$.

development equals one if the alternative $i$ is chosen by individual $n$ in choice situation $s$, and 0 otherwise. In this paper, the Halton draw approach was used to generate the random draws. Besides, we systematically evaluated the model by increasing the number of draws from 100 to 1000 to make a trade-off between the computation time and estimation stability. The final estimation results reported later are based on 500 Halton draws.

Table 4

| Attribute | Alternative | Multinomial Logit Model | Error Component Latent Class Model |
|-----------|-------------|-------------------------|-----------------------------------|
|           | Estimate    | t-statistics            | Estimate | t-statistics | Estimate | t-statistics |
| Travel context | | | | | | |
| COVID-19 restrictions policy | | | | | | |
| Lockdown Level 3 | Not travel | 1.07*** | 14.1 | 2.09*** | 9.79 | 2.5*** | 3.73 |
| Lockdown Level 2 | Not travel | 0.426*** | 5.23 | 0.534*** | 3.13 | 1.21** | 2.06 |
| Lockdown Level 1 | Not travel | -0.244*** | -2.64 | -0.676*** | -3.77 | -0.168 | -0.373 |
| Totally open | Not travel | -1.252 | - | -1.95 | - | -3.54 | - |
| Travel Purpose | | | | | | |
| Work | Not travel | -0.209** | -2.45 | -0.589*** | -3.12 | 0.817 | 1.64 |
| Social | Not travel | 0.237*** | 2.91 | 0.346* | 1.87 | 0.869* | 1.87 |
| Shopping | Not travel | -0.181** | -2.16 | -0.18 | -0.903 | -0.945* | -1.86 |
| Leisure | Not travel | 0.153 | - | 0.42 | - | -0.74 | - |
| Alternative-specific attributes | | | | | | |
| Travel cost ($) | Bus, Car, and SEB | -0.178** | -2.16 | -0.267** | -2.2 | -0.048 | -0.307 |
| Travel time (min) | All modes | -0.304*** | -6.15 | -0.277*** | -3.07 | -0.522*** | -4.4 |
| Out-of-vehicle time (min) | Bus | -0.335 | -1.12 | -0.425 | -0.8 | -0.482 | -0.553 |
| Requirement of Facemask | Bus | 0.009 | 0.129 | -0.173 | -1.42 | 1.28 | 0.526 |
| 1.5-m social distance rule | Bus | -0.049 | -0.721 | -0.156 | -1.24 | 1.24** | 2.04 |
| Offering hand rubs | Bus | -0.0381 | -0.562 | 0.103 | 0.845 | -0.23 | -0.555 |
| Onboard passengers’ limitation (%) | Bus | 0.16 | 1.44 | 0.025 | 0.128 | 3.62** | 2.26 |
| 25% of the total seats | Bus | 0.058 | 0.503 | 0.258 | 1.25 | -1.54 | -0.638 |
| 50% of the total seats | Bus | -0.045 | -0.375 | -0.0812 | -0.388 | -0.288 | -0.116 |
| 75% of the total seats | Bus | -0.1731 | - | -0.20 | - | -1.79 | - |
| Disinfection frequency | | | | | | |
| Every journey | Bus | 0.138 | 1.23 | 0.209 | 1.1 | 3.59 | 0.743 |
| Once per 4 journeys | Bus | 0.19* | 1.72 | 0.379* | 1.9 | 4.48 | 0.945 |
| Once per 8 journeys | Bus | -0.198 | -1.55 | -0.502** | -2.15 | -4.52 | -0.94 |
| Once a day | Bus | -0.13 | - | -0.09 | - | -5.55 | - |
| ASCs | | | | | | |
| Constant 1 | Car | 0.494*** | 4.13 | 2.92*** | 3.08 | 5.26*** | 3.17 |
| Constant 2 | Bus | -0.781*** | -3.58 | -1.27 | 0.968 | -9 | -0.507 |
| Constant 3 | Bike | 1.38*** | 15.3 | 3.4*** | 4.47 | 5.78*** | 2.75 |
| Constant 4 | SEB | -2.12*** | -11.3 | -0.02 | -0.0218 | -0.221 | -0.137 |
| Constant 5 | Walk | 0.311 | 1.46 | 3.08*** | 3.43 | 4.81*** | 2.79 |
| SD of the random panel effect parameter | | | | | | |
| Deviation 1 | Car | - | - | 6.69*** | 3.57 |
| Deviation 2 | Bus | - | - | 1.17 | 1.04 |
| Deviation 3 | Bike | - | - | 7.5*** | 3.2 |
| Deviation 4 | SEB | - | - | 2.48* | 1.9 |
| Deviation 5 | Walk | - | - | 5.04*** | 2.6 |
| Error components for nests of alternatives parameters | | | | | | |
| Component Deviation | Share Space | - | - | 2.19* | 1.82 |
| Class membership | | | | | | |
| Constant | - | - | 21.8*** | 4.83 | 0 (fixed) |
| Education level (-1: HAVO/VWO and below, 1: Bachelor degree or above) | - | - | -4.31*** | -3.98 | 0 (fixed) |
| Gender (1: male, -1: female) | - | - | 2.03*** | 3.24 | 0 (fixed) |
| Job (-1: employed, 1: unemployed/retired) | - | - | -0.244 | -1.37 | 0 (fixed) |
| Marital (-1: single or couple with no children, 1: couple with one or more children) | - | - | -2.38*** | -3.69 | 0 (fixed) |
| Age (years) | - | - | -0.877*** | -4.79 | 0 (fixed) |
| Class probability | - | - | 0.597 | 0.403 |
| Goodness-of-fit | | | | | | |
| LL | -4430.977 | -4311.537 |
| # of observations | 3152 | 3152 |
| # of parameters | 23 | 58 |
| $R^2$ | 0.215 | 0.262 |
| $\rho^2$ | 0.211 | 0.252 |

Note: SEB means shared E-bike *** Estimates whose p-value are less than 0.01. ** Estimates whose p-value are less than 0.05. * Estimates whose p-value are less than 0.10.
5. Results and discussion

Table 4 presents the results of the error component latent class (ECLC) model and a base model (e.g., classical Multinomial logit model). Note that all categorical variables were effect-coded before estimating the model. In addition, because effect coding can test all category means against one overall mean value, the last category of each categorical variable was set as the reference category in this paper (Hardy, 1993). To identify the optimal number of classes for the ECLC model, the BIC values for several alternative ECLC models, in which the number of classes ranges from 2 to 5, were calculated. The 2-class model has the minimum value of the BIC and therefore it was identified as the best model and presented in further analyses.

Overall, both models have a good fit. The loglikelihood (LL) value increased from $-4430.977$ (base model) to $-4311.537$ (ECLC model). In addition, the ECLC model leads to a slightly higher adjusted Rho-squared ($\rho^{-2}$) value (0.252) than the base model (0.211), implying that taking the taste and preference heterogeneity into consideration could effectively improve the goodness-of-fit.

Moreover, estimation results in Table 4 show that parameter signs for both models are almost the same. The parameter for the error component is statistically significant, indicating that a noticeable heterogeneity is associated with the features of space-sharing. Lastly, since the ECLC model performs better than the base model, the later section will discuss the results, mainly focusing on the ECLC model.

It is shown that most parameters in the two classes of the ECLC model have the same and expected signs. However, there are some exceptions. For example, some COVID-19 related policies adopted by the public sector, like the 1.5 m distance rule and onboard limitation of the number of passengers, have a significantly positive effect on the adoption of public transport in class 2 while present insignificantly negative impacts in class 1. These results have some interesting features in understanding the taste variation in traveling of shared spaces and vehicles under the COVID-19 pandemic and will be discussed later in more detail.

5.1. Nest effect and class membership model

The result for examining nest effect (i.e., the error component) is listed in Table 4. The estimate of the standard deviation for the error component is significant, suggesting that heterogeneity in the preferences of transportation modes with space-sharing features across individuals is high, e.g., some respondents are still willing to use public transport under the pandemic, whereas others would never consider the public transportation modes and exclude them from their choice set.

As presented in Equation (3), personal attributes were used to define the individual-specific variables of membership function in the ECLC model. Thus, respondents who have different characteristics may have different preferences and be allocated to different classes. Table 4 reports the estimation results of the class membership function that was conducted to determine the probability of individual $n$ belonging to latent class $r$. In the case of the ECLC model, the second class was treated as the reference.

As presented in Table 4, the estimate of education in the membership function is $-4.31$, providing an evidence that class 1 primarily consists of respondents with low education (HAVO/VWO or below) and class 2 respondents having higher education (HBO/VO and Master/Ph.D.). In line with this, the results also show that older people are more likely to belong to class 2. Moreover, the negative parameter for marital status confirms that married couples with kids probably belong to class 2. This class contains about 40.9% of the sample.

Quite the opposite, respondents who have jobs (regardless of full-time or part-time jobs) are probably a member of class 1. In addition, single and married respondents but without children have a higher probability of being in class 1. Estimates of gender and age suggest that young males are more likely to be in the first class. This class contains about 59.7% of the sample.

Based on the results of other attribute parameters, several differences between the two classes could be highlighted. First, class 1 shows more concerns about disinfection frequency. Second, class 2 is more concerned with the physical distance from others in public transportation modes. These results are in line with the results reported in previous studies that highly educated respondents and the elderly are more concerned with government policies (Zhang et al., 2021).

5.2. Effects of COVID-19 countermeasures and travel purpose

Looking at the parameters of the COVID-19 restrictions policy obtained per class, it could be found that both classes are sensitive to the changes of lockdown levels. The results suggest that the two classes have a similar response pattern in the sense that the average Dutch citizen tends to get out of the house if no lockdown is announced or the lockdown level is low(e.g., Lockdown Level 1). Also, travel suspension will be the preferred option when the Dutch government takes stricter measures to prevent the spread of COVID-19 (i.e., the lockdown level increases to a higher level).

In the case of the strength of effects between two classes, results show that class 2 has larger coefficients for not traveling in all lockdown levels than class 1. This means that class 2 is more sensitive to the severity of the pandemic relative to class 1. The results are consistent with common sense because class 2 primarily consists of older and higher educated people, as well as married couples with kids. These are all among the groups most severely affected by the COVID-19. It is also observed that both classes put the highest positive weight on the highest lockdown level, indicating that the strictest lockdown does get people to notice the severity of the epidemic.

Regarding the effects of travel purpose, the results indicate that class 1, in which people who have a job are over-represented, puts a negative weight on work at home. This finding is surprising, to a certain degree, in light of the fact that constraints and regulations imposed by employers will be decreased for working from home, compared to working in the office. In contrast, class 2, in which highly educated and older people are somewhat over-represented, is not sensitive to this attribute. On the other hand, class 2 is more sensitive to the variable shopping, indicating that class 2 (i.e., older people) prefers to shopping in physical stores rather than online. This is understandable because physical grocery shops are usually easier acquired for the elderly. In addition, because of the high infection risk, both classes seem to be reluctant to enjoy social activities during the pandemic.

5.3. Effects of alternative-specific attributes

According to our results, time-related attributes influence the probability of transportation mode selection. As expected, travel time is found to significantly negatively impact all transportation modes in both classes, such that people prefer to choose a means of transportation that has minimal travel time when they are traveling. This finding corresponds well with many previous studies (Kim et al., 2017; Guo et al., 2020). Similarly, out-of-vehicle time is also found to have a negative impact on the utility of public transport. However, the parameter is statistically insignificant based on our current data. Regarding the differences in responding to travel time and out-of-vehicle time between the two classes, class 2 is more sensitive to time-related attributes than class 1. This finding may be the result of the high risk of infection in open spaces. Older people and married couples with kids are more willing to choose the mode of transport which has the minimal travel time to reduce the risk of COVID-19 infection.

Furthermore, our results indicate that the sensitivity to travel cost in the two classes is not the same. As presented in Table 4, class 2 does not put significant weight on this attribute. Although the parameter is not significant, the negative sign of travel cost in both classes reveals that the decrease of travel cost for cars, buses, and shared E-bikes might attract individuals to use them. In addition, the result that travel cost is
statistically insignificant in class 2 is in line with intuition. That is because the elderly is known to be much more likely to die from infection with the COVID-19. Compared with cheap transportation modes, they are more focused on travel safety.

After the outbreak of COVID-19, the Dutch public transport sector took several measures to ensure safe travel. The specific focus of this part concerned the question of whether the measures adopted by the Dutch public transport sector are helpful to rebuild trust in public transport.

For the attribute, face-mask requirement, the results show that, though the estimates are not statistically significant, the differences in the preference between the two classes can still be found. The positive sign for class 2 (i.e., older and higher educated people) suggests that this measure positively affect the use of public transport for the elderly. Quite the opposite, it is more interesting that respondents who belonged to class 1 are resistant to the mandatory measures published by the authorized departments. Although this kind of measure might help strengthen the protection of themselves, they are still unwilling to follow the regulation, and for that reason, they refuse to use public transport. Similar results could also be found for the attribute, 1.5-m distance rule. The estimated parameter for class 2 is also statistically significant.

Regarding the allowed number of passengers, results reveal that the estimated coefficients for class 2 monotonically increase with the decrease of the allowed number of passengers. That indicates that respondents who belonged to class 2 are sensitive to the number of on-board passengers in the sense that the probability of using public transport increases if the allowed number of passengers decreases. The estimates in class 1 are similar to those of class 1, except for the first category, but this parameter is insignificant.

The results also show that the disinfection frequency has significant effects on the choice of public transport for class 1. Although the estimates for class 2 are not significant, their signs are in line with those of class 1. Results show that the parameters are negative when the disinfection frequency is greater than or equal to once per 8 journeys. Quite the opposite, the parameters become positive when the disinfection frequency reaches once per 4 journeys, indicating that individuals are more likely to use public transport if buses are frequently cleaned and sanitized.

Based on the analysis above, combined with the characteristics of respondents, the general effect of COVID-19 related policies could be analyzed. The older and highly educated people are more susceptible to enforcement measures (e.g., face-mask requirement and 1.5-m distance rule). They believe these enforcement measures could help enhance the safety of using public transport. In contrast, young and single respondents are more accessible to non-compulsory measures (e.g., disinfection frequency) and have resisted enforcement measures. It is also a sideshow that protestors in recent anti-COVID rules protests in the Netherlands are mainly young people. Broadly speaking, the results indicate that the Dutch government should not only focus on publishing enforcement measures but also take adequate steps to use the power of non-compulsory measures to prevent the spread of COVID-19 and rebuild confidence in public transport. More specifically, the enforcement and non-compulsory measures could be designed with respect to population groups. Enforcement measures may get significant responses from older and highly educated people, married couples with children, especially females. Contrast this with individuals who are single males or have no children and with low educational background expressing concerns about the non-compulsory measures.

The estimated results of the alternative-specific constants (ASCs) show that all parameters in both classes are as expected. The positive values for car, bike, and walk indicate that respondents prefer private transport modes over other shared modes under the COVID-19 pandemic. This finding is consistent with previous empirical studies in other cities; for instance, there is compatible agreement on a rising status of the car and aura-faded public transport in the pandemic (Eisenmann et al., 2021). Furthermore, the bike is the most attractive transportation mode for both classes. This result also confirms our shared experience that bike is the most fashionable form of transport modes in The Netherlands.

To explore the potential causes behind the taste variation in COVID-19 countermeasures, we also tested a series of ECLC models, where class membership was determined by the factors other than sociodemographic variables. For instance, we estimated a model where the class membership was determined by the decrement of trips for shopping, leisure, work, and social activities during the outbreak of COVID-19. However, the results showed that none of these variables significantly affect the class membership and neither on the importances of various COVID-19 countermeasures. We also tested the model where class membership was related to whether or not a respondent has a relative who was infected by COVID-19. In the sample, 63.6% of the respondents expressed that this was the case. Using the variable as the predictor variable of the class membership model, the ECLC model was estimated, and the results are also presented in Appendix Table S1. It can be found that respondents whose relatives had been infected by the COVID-19 were significantly more likely to belong to class 1, which is sensitive to the changes in COVID-19 countermeasures. In contrast, class 2, in which most respondents did not report their relatives had been tested positive for the COVID-19, was reluctant to those compulsory measures adopted by the public transport sector. These results are also in line with intuition. Respondents cannot sufficiently imagine the severity of the pandemic, which differs from their own perspectives. Respondents whose relatives had been infected by the COVID-19 know well the potential risks. In contrast, respondents who had no infected relatives cannot sufficiently imagine the risk.

6. Policy implications

Facing the unexpected COVID-19 crisis, policymakers worldwide need to develop innovative measures to prevent the spread of the virus, based on a large number of considerations and limited by the desire and compliance of people. Indeed, the results of our study are just the tip of the iceberg. We must acknowledge that our research still remains great gaps for improvement. In particular, the data used in this manuscript was collected at a specific time and in a specific context. It follows that the generic applicability of our results is limited. Despite this limitation, we still believe that the results in this paper can be helpful in designing effective COVID-19 countermeasures in countries with a similar context.

First, upon careful inspection of the results for the two ECLC models, it can observe that most of the participants in our survey tend to comply with both the policies and measures announced by the central government and corresponding regulatory authorities. Although the policies adopted by the central government play the most prominent role in adjusting citizens’ travel behavior, other protective measures published by the relevant department (e.g., public transport sector) also seem to affect the Dutch travel choice behaviors. This suggests that a broad series of policies and measures, taking into every aspect of the Dutch lives, could effectively reduce the infection risk. Nonetheless, our results present that nearly 60% of our sample show reluctance to adhere to these compulsory protective measures announced by the public transport sector, indicating that relevant government departments should to be careful in their policy design and how these compulsory measures could be recommended to the society.

Secondly, our results entitle policymakers to identify the degree of social support for these COVID-19 countermeasures. Simultaneously, the strength of impacts on the travel choices could also be examined. For instance, based on the estimated parameters, the ECLC model could be used to determine the percentage of people who support the 1.5-m social distance rule. In particular, the model results will help identify which COVID-19 countermeasure will be effective in restoring the confidence in the use of public transport.

Thirdly, the effectiveness of policies or measures can be assessed for different of people. This reference group could be the direct relevant stakeholder or the broad masses. For this, it is essential to specify the
reference group in terms of (a selection of) socio-demographics, exploring the potential causes behind the preference heterogeneity. New angles and strategies could be offered for policy makers to design customized policies for specific population groups.

Fourthly, the value of travel time (VTT) is an essential concept in designing policies in transport because this indicator could convert travel time changes into monetary benefits. Using this paper’s advanced discrete choice model, the values of time, depending on the travel contexts and personal attributes of the respondents, could be estimated. Taking the estimates of the classic Multinomial Logit model as an example, this paper found that the average value of time in the population under the COVID-19 pandemic is 1.7 euros per minute. Compared to the recommended VTT of 8.75 euros per hour in the context of the 2010 Dutch national travel survey (de Jong and Kouwenhoven, 2019), our estimate is significantly higher, implying that the respondents are willing to sacrifice additional cost burden in order to shorten their travel time. It is worth pointing out that, unlike the usual situation where travel cost are the main factors affecting travel decisions, the uncertainty hiding behind the behavior change of public transport users in a pandemic might be greatly affected by the infection risk because a longer travel time means a higher COVID-19 infection risk. This could also partially explain that our estimate is higher than the number found in previous studies. For further analysis, the ECLC model could also be used to consider the unobserved value of time differences in the population and the influence that each respondent answered multiple-choice tasks (i.e., the panel effect).

Finally, our results enable policy makers to determine the willingness of people to accept a higher ticket price for reducing the COVID-19 infection risk onboard. Taking the model presented in Section 5 as an example, our results indicate that the sample in class 1 weighs a more frequent cleaning and disinfecting (e.g., once per 4 journeys) as heavily as a one-off ticket price increase of 1.42 euros. This indicates that the whole country (which has nearly fourteen million citizens aged older than 15 years old) could accept an additional ticket price burden of approximately 12.4 million euros. Therefore, this “value of risk” estimate allows policy makers to design subsidy-mechanism for public transport in order to ensure travel safety during the pandemic and, at the same time, avoid placing an undue burden on the travelers.

Before deducing the conclusions for other countries and future situations, it is also necessary to assess the spatial transferability of the results obtained in this paper. In the case of spatial transferability, we have observed considerable differences across countries concerning culture, the severity of the pandemic, and the governments’ protective-behavior policies against COVID-19. The relative weights attached to different attributes, therefore, will also vary across countries. Moreover, some COVID-19 countermeasures considered in this experiment are not be adopted by some countries, while some policies excluded in this study are implemented in some geographical contexts. Nonetheless, recent studies on the worldwide assessment of COVID-19 pandemic policy indicated an intersection-based combination of responses from governments around the world (Hale et al., 2020; Petherick et al., 2021). Given these similarities, we feel that our results could also hold lessons (at least) for the geographical contexts with similar pandemic policies.

Regarding the temporal transferability, we could prognosticate that the latent preferences and tradeoffs of citizens may change according to the situation (e.g., the risk level of the virus). The response of people to policies may also differ by time, e.g., fatigue, vaccinations. Although this study has added a constant variable, ‘COVID-19 restrictions policy’, to consider the various “stages” of the pandemic and related policies, it is undoubtedly more desirable to test these dynamics by repeating our experiment in due course. Despite this, these timely estimates for the COVID-19 countermeasures are also helpful for policymakers in the short term to understand the policies’ effectiveness and make adjustments for the changes.

In any case, we hope the findings of our study could be the stepping stones for future study efforts to investigate the effectiveness of COVID-19 countermeasures in different countries (triggered by the pandemic or other public health emergencies).

7. Conclusions and future study

The COVID-19 pandemic had dramatically changed the worldwide transportation patterns in 2020. Everyone in the world was forced to change their travel habits and travel behaviors. Due to both restriction policies and fear of infection, travel demand has dropped greatly. As the epidemic continues, some individuals have been accustomed to use private vehicles to avoid the shared transportation modes (e.g., public transport), while other have started to try shared bikes and E-bikes. Previous studies, however, did not sufficiently present evidence yet on the heterogeneous preference of people when facing many mobility options under the pandemic. The underlying reasons for these behavioral changes are also not fully understood. Therefore, understanding individuals’ travel decision-making in the pandemic could illuminate how the COVID-19 pandemic changed the travel decisions and, more importantly, provide governments with practical policy recommendations for the COVID-19 and future pandemics. This study takes The Netherlands as an empirical context and presents the empirical results of travel decisions after the outbreak of COVID-19. Based on the stated preference data collected in December 2020, an error component latent class model was estimated to identify the taste variation and the possible correlations between homogeneous alternatives. Looked from the overall, we found that the willingness to travel during the COVID-19 pandemic is weakened. People prefer to stay at home and only make a trip when it is necessary. The findings are in line with many recent studies in which the number of trips is found dramatically reduced due to the “intelligent lockdown” (de Haas et al., 2020). An interesting finding of this study is the significant heterogeneity within the society in terms of the impacts of COVID-19 pandemic countermeasures and shared vehicles. First, some respondents appear to focus on the enforcement measures while ignoring other non-compulsory measures. Quite the opposite, other respondents appear to put much weight on the non-compulsory measures and are unwilling to comply with enforcement measures. Second, while most respondents dislike public and shared mobility options, a sizeable minority still wants to try these shared services. In fact, the findings of highly heterogeneous travel preferences are not surprising because the COVID-19 related policies created a storm of controversy. The results are also in line with findings in other COVID-19 related studies.

Although significant heterogeneous dependencies between COVID-19 related policies and travel decisions have been found in this study, it is needed to further investigate the long-term effects of the COVID-19 pandemic from a longitudinal perspective. The psychological response is dynamic in nature, and it constantly affects people’s emotions and decisions. As an extension to the current study, more psychological factors and latent attitudes might also be considered. Besides the taste variation between different segments of people, the systematic heterogeneity may also be examined when the data size is big enough. In addition, as discussed in Section 3.2, the samples are still not fully bias-free. In future studies, a more balanced sample seems more appealing. Moreover, the current study is built based on only experimental data, and a comparative analysis based on both historical and experimental data will offer additional insights. Lastly, because the role of public transport may differ in cities with different car ownership rates, it is also interesting to extend the current study by exploring the travel preferences in different spatial scales, especially in developing countries.

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Appendix A. Supplementary data

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