A Multinomial Probit Analysis of Shanghai Commute Mode Choice

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ABSTRACT

Commute trips account for a large portion of travel demand in peak hours and significantly influence the operation of urban transportation systems. In this paper, we apply a fully flexible multinomial probit (MNP) model for the analysis of commute mode choice behavior, and compare this MNP model with more traditional discrete choice models, including the multinomial logit (MNL), the cross-nested logit (CNL), the heteroscedastic independent MNP (HI-MNP), and the homoscedastic non-independent MNP (HONI-MNP). The two-variate bivariate screening (TVBS) approach, a recently developed analytical evaluation for the multivariate normal cumulative distribution (MVNCD) function, is employed. The sample for analysis is drawn from a web-based travel survey conducted in Shanghai. Overall, from a data fit perspective at, both the disaggregate and aggregate levels, the MNP clearly outperforms all the other four models, underscoring the importance of considering both heteroscedasticity as well as correlated error terms when estimating mode choice models. Policy implications are also examined and discussed.

Keywords: mode choice, multinomial probit (MNP) model, multivariate normal cumulative distribution (MVNCD), two-variate bivariate screening (TVBS) approach, cross-nested logit (CNL) model

1. INTRODUCTION

The emergence of travel smartphone app-facilitated modes, and the increasing ease in the ability to plan, schedule, and pay for journeys undertaken by different modes, have led to increased accessibility to activity locations, especially in urban areas. While the effects of such technology-enabled travel planning and execution on urban traffic congestion are still being examined (see, for example, Dias et al. (2017), Lavieri and Bhat (2019), Shaheen and Cohen (2019), Zhong et al. (2018)), traffic congestion continues to clog urban streets in many cities during the commute peak periods, especially in large metropolitan areas of China. This is not surprising, because commute trips account for a large portion of daily trips and are concentrated during relatively narrow windows of time corresponding to work start and end times. For instance, 48% of average daily trips in Shanghai in 2015 were commute trips, and the traditional 9 am-5 pm work day packs those trips during the 7-9 am time window in the morning and the 5-7 pm time window in the evening (2015). Thus, commute mode choice analysis plays an important role in urban transportation planning, providing a tool to evaluate the ability of traffic congestion mitigation efforts to effect a change in the mode of travel from solo-auto to high-occupancy vehicles. The efforts to relieve traffic congestion may involve improvement in the level of service (LOS) attributes of high-occupancy travel modes (for example, designation of high-occupancy vehicle lanes on freeways and an increase in the frequency of bus service), disincentives to use the solo-auto mode (for example, congestion-pricing and additional gas taxes), and encouragement of the use of non-motorized travel modes (for instance, providing separate bicycle lanes and well-lit walk paths).

Most commute mode choice models are based on the random utility maximization (RUM) framework of microeconomic theory, which assumes that an individual's choice of mode on any choice occasion is a reflection of underlying indirect utilities associated with each of the available modes and the individual selects the alternative which provides her or him the highest utility (or least disutility). The most commonly used RUM model structure in mode choice practice is the multinomial logit (MNL) model (McFadden, 1974), which has a simple mathematical structure and provides a closed-form likelihood function that is easy to compute. But the MNL model assumes that random error terms across the utilities of alternatives are independently identically distributed (IID) with a Gumbel distribution. This assumption leads to the independence from irrelevant alternatives (IIA) property at the disaggregate choice level, which results in equivalent cross-elasticities across alternatives.

To overcome the limitation of IIA property, the nested logit (NL) model (Ben-Akiva and Lerman, 1985; Daly and Zachary, 1978; McFadden, 1978; Williams, 1977) was proposed, which relaxes the independence across utility error terms of the MNL model, allowing for correlations across similar alternatives. Alternatives in a nest exhibit an identical degree of increased sensitivity relative to alternatives not in the nest (Bhat, 2003a). A problem with the NL model is that it requires the *a priori* specification of the nesting structure. This requirement has at least two drawbacks. First, the number of different structures to estimate in a search for the best structure increases rapidly as the number of alternatives increases. Second, the actual competing structure among alternatives may be a continuum that cannot be accurately represented by partitioning the alternatives into mutually exclusive subsets. A suite of more general multivariate extreme-value (MEV) models were proposed and applied to allow more flexible correlation structures than the NL model. These include the paired combinatorial logit (Chu, 1989; Koppelman and Wen, 2000) , the ordered generalized extreme value (OGEV) model (Small, 1987), the MNL-OGEV model (Bhat, 1998a), and the cross-nested logit (CNL) (Ben-Akiva and Bierlaire, 1999; Vovsha, 1997; Wen and Koppelman, 2001). Of these MEV models, the CNL model is the most flexible. Also, all these MEV models have a closed-form structure; however, they require all correlations to be non-negative. GEV correlation estimates are biased in the presence of negative correlations between choice alternatives (Dong et al., 2017). In addition, all the MEV models impose the *a priori* assumption of homoscedasticity of the utility error terms across alternatives. On the other hand, Bhat (1995) proposed the heteroscedastic extreme value (HEV) model, which allows the utility error terms to be heteroscedastic across alternatives, but maintains independence across alternatives.

In the more recent past, two general econometric model structures have been commonly used in the literature that are much more flexible than all of the models just discussed. The first corresponds to an MEV kernel structure mixed with a multivariate distribution to engender flexible covariance structures across the utilities of alternatives. While many multivariate mixing distributions may be used based on the context, it is quite typical to use a multivariate normal mixing distribution (though more recent studies have used a variety of non-normal and even discrete distributions; see, for example, Bhat and Lavieri (2018); Train (2016); Vij and Krueger (2017)). The classic mixed MEV model is the normally-mixed multinomial logit (MMNL) (Bhat, 1998b; McFadden and Train, 2000; Revelt and Train, 1998). The second general model structure is the multinomial probit (MNP) model (Daganzo, 1980). Both structures have been used in the past, with the choice between a GEV kernel or an MNP kernel really being a matter of "which is easier to use in a given situation" (Ruud, 2007). But, in the past two decades, the mixing of the normal with the GEV kernel has been the model form of choice in the economics and transportation fields, mainly due to the relative ease with which the probability expressions in this structure can be simulated (see Bhat et al. (2008) and Train (2009) for detailed discussions). On the other hand, an MNP kernel has not been used as much, because the simulation estimation of the MNP is generally more difficult. In any case, while there have been several approaches proposed to simulate the models with a GEV or an MNP kernel, most of these involve pseudo-Monte Carlo or quasi-Monte Carlo simulations in combination with a quasi-Newton optimization routine in a maximum simulated likelihood (MSL) inference approach (Bhat, 2003b, 2001). In such an inference approach, the desirable asymptotic properties are obtained at the expense of computational cost (because the number of simulation draws has to rise faster than the square root of the number of observations used for estimation). Moreover, the MSL estimation and inference can be affected by simulation noise, which might cause problems ranging from non-convergence to inaccuracy and/or non-inversion of the Hessian of the log-likelihood function.

More recently, there has been renewed interest in the use of the MNP model, thanks to the development of new analytic methods to estimate the multivariate normal cumulative distribution (MVNCD) function (Bhat, 2018). Patil et al. (2017) show that these analytic approaches can be much faster than traditional MSL approaches used for the MMNL or MNP models. But these analytic approaches are much more suited to the MNP model. Given this computational advantage in using the MNP model, we will focus in this paper on alternative MNP models and compare them with MNL and CNL models, two types of MEV models being widely used in practice.

1.1 The Current Research

Due to estimation difficulty, the MNP model has rarely been applied for mode choice modeling, in both research and practice. This is especially the case for commute mode choice models estimated in Chinese cities, most of which are based on the MNL model (Dai et al., 2016; Feng et al., 2014; Hu et al., 2018; Li and Zhao, 2015; Lin and Chang, 2010; Song et al., 2012; Sun et al., 2017; Yang et al., 2016, 2017; Zhao, 2011). The rare exception to this long list of MNL studies are Lin and Chang (2010) and Yang et al. (2013), who estimate an NL or CNL model. Besides, most applications of commute mode choice in the literature use three or four alternatives, while, in Chinese cities, there are usually more than four alternatives with non-insignificant commute mode shares (for example, car, taxi, bus, metro, bicycle, walking, a combination of bus and metro, and other kinds of combinations of different modes).

In this paper, we demonstrate the use of the MNP model for mode choice modeling even with a relatively large number of alternatives. Indeed, there is no need to shy away today from the MNP model on any grounds, computational-wise or otherwise. We use data on commuter travel from the City of Shanghai in China to estimate an MNP model with six alternatives, which is estimated using an analytic approximation for the MVNCD function as proposed by Bhat (2018). Bhat develops and compares several matrix-based methods for the analytical evaluation of the MVNCD function, and recommends the two-variate bivariate screening (TVBS) approach as the one-stop evaluation approach for the MVNCD function. This is the specific analytic approximation method used in the current paper.

The results from the MNP model are compared with the more traditional models, including the MNL, the CNL, the homoscedastic non-independent MNP (or the HONI-MNP, which is similar to the CNL, except that it uses a multivariate normal kernel rather than the multivariate Gumbel kernel in the CNL, and allows for negative utility correlations across alternatives), and the heteroscedastic independent MNP model (or the HI-MNP model, which is similar to Bhat's HEV model (Bhat, 1995), except using heteroscedastic normal distributions instead of heteroscedastic Gumbel counterparts). The assumptions of these models compared with the MNP model are summarized in **Table 1**. In addition to data fit considerations, policy implications and disadvantages of using the traditional models relative to the fully flexible MNP model are examined and discussed.

Table 1 Assumptions of models

Models	**Assumptions regarding stochastic component of the utilities of alternatives**
MNL	Identical and independent; Gumbel
CNL	Identical, with only positive correlations allowed; Gumbel
HI-MNP	Non-identical, but independent; Normal
HONI-MNP	Identical, but non-independent; Normal
MNP	Non-identical, non-independent; Normal

The rest of the paper is structured as follows. The next section presents the structure of the CNL model (the MNL is a special case of the CNL) and the MNP model (the HI-MNP and HONI-MNP models are special cases of the MNP). It also provides a brief introduction to the TVBS approach. Section 3 discusses the data used in the empirical study. Section 4 reviews the results from the different models, and compares the data fit as well as policy implications from the different models. The final section concludes this paper and identifies directions for additional research.

2. MODELING METHODOLOGY

2.1 The Cross-Nested Logit (CNL) Model

The CNL model allows each available mode to belong to more than one nest, thus generalizing the NL model that restricts each mode to belong exclusively to one and only one nest. Based on the MEV theory (Ben-Akiva and Bierlaire, 1999; McFadden, 1978; Vovsha, 1997; Wen and Koppelman, 2001), the probability of choosing mode i in the CNL model is as follows:

$$P_i = \sum_m P_m \cdot P_{i|m} = \sum_m \left(\frac{\left(\sum_{i \in N_m} \left(\alpha_{im} e^{V_i} \right)^{1/\mu_m} \right)^{\mu_m}}{\sum_m \left(\sum_{i \in N_m} \left(\alpha_{im} e^{V_i} \right)^{1/\mu_m} \right)^{\mu_m}} \cdot \frac{\left(\alpha_{im} e^{V_i} \right)^{1/\mu_m}}{\sum_{i \in N_m} \left(\alpha_{im} e^{V_i} \right)^{1/\mu_m}} \right), \tag{1}$$

where P_m is the marginal probability of nest m, $P_{i|m}$ is the conditional probability of choosing alternative i in the nest m. α_{im} is the allocation parameter that allows mode i to be assigned partially to nest *m*, $0 \le \alpha_{im} \le 1$ and $\sum_{m} \alpha_{im} = 1$. When $\alpha_{im} = 0$, alternative i is not in the nest m. By assigning only binary values to α_{im}, an alternative can only belong to one nest, as in the NL model. N_m is the set of all modes included in nest *m*. μ_m is the dissimilarity parameter for nest m capturing the correlation between modes in nest *m*, and $0 < \mu_m \le 1$. The correlation between modes in nest *m* increases as μ_m gets closer to zero, and decreases as μ_m approaches 1. When μ_m is equal to one for all m nests, the CNL model collapses to the MNL model.

To better understand error correlations among different modes, correlations of the CNL model can be calculated as per the following equation (Marzano et al., 2013):

$$\rho_{\varepsilon_i,\varepsilon_j} \approx \sum_m \alpha_{im}^{\frac{1}{2}} \alpha_{jm}^{\frac{1}{2}} \left(1 - \mu_m^2\right) \tag{2}$$

where ε_i and ε_j are the error terms in the utility functions of mode i and j, respectively; α_{jm} is the allocation parameter of mode j to the nest m.

2.2 Multinomial Probit (MNP) Model

This section provides an overview of the MNP modeling methodology and formulation. The utility U_{in} that an individual $n\left(n = 1, 2, ..., N\right)$ obtains from mode $i\,(i = 1, 2, ..., J)$ can be expressed as:

$$U_{in} = \mathbf{X_{in}\beta} + \varepsilon_{in} = V_{in} + \varepsilon_{in} \tag{3}$$

where $\mathbf{X_{in}}$ is a $(1 \times K)$ vector of explanatory variables characterizing both mode i and individual n (including a constant for each alternative, except one of the alternatives); $\boldsymbol{\beta}$ is a $(K \times 1)$ coefficient vector corresponding to variable vector X_{in}. V_{in} is the systematic utility. ε_{in} is the random error term. We assume that $\boldsymbol{\varepsilon}_n = \left(\varepsilon_{1n}, \varepsilon_{2n}, ..., \varepsilon_{Jn}\right)$ is normally distributed with zero mean and a covariance matrix that can be expressed explicitly as $\Omega = \begin{bmatrix} \sigma_{11} & \sigma_{21} & \cdots & \sigma_{J1} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{J2} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{J1} & \sigma_{J2} & \cdots & \sigma_{JJ} \end{bmatrix}$.

The MNP model with J alternatives $\left(J > 2\right)$ has $J(J+1)/2$ elements in the covariance matrix, and $[J(J-1)/2]-1$ covariance parameters are identified when normalized. When the J random error terms are assumed to be independent, the MNP model collapses to the HI-MNP (heteroscedastic independent MNP) model. All the covariances are zero and $(J-1)$ variances in the covariance matrix can be identified. When the J random error terms are assumed to have the same variance, the MNP model collapses to the HONI-MNP (homoscedastic non-independent MNP) model.

Individuals are assumed to choose the travel mode with the greatest utility. The probability that an individual n will choose mode i is the probability that mode i has a greater utility than all the other modes in the choice set. Therefore,

$$P_{in} = P\left(U_{in} > U_{jn}\right) = P\left[\left(\varepsilon_{jn} - \varepsilon_{in}\right) < \left(\mathbf{X_{in}\beta} - \mathbf{X}_{j\mathbf{n}}\boldsymbol{\beta}\right)\right],\ j = 1, 2, ..., J;\ j \neq i \tag{4}$$

Let $\varepsilon^*_{jn} = \varepsilon_{jn} - \varepsilon_{in}$ and $V^*_{jn} = \mathbf{X_{in}\beta} - \mathbf{X}_{j\mathbf{n}}\boldsymbol{\beta}$ with $\forall j \neq i$, then

$$P_{in} = P\left(\varepsilon^*_{jn} < V^*_{jn}\right) = \int_{-\infty}^{V^*_{1n}} \int_{-\infty}^{V^*_{2n}} ... \int_{-\infty}^{V^*_{jn}} ... \int_{-\infty}^{V^*_{Jn}} f\left(\varepsilon^*_{1n}, \varepsilon^*_{2n}, ..., \varepsilon^*_{jn}, ..., \varepsilon^*_{Jn}\right) d\varepsilon^*_{1n} d\varepsilon^*_{2n} ... d\varepsilon^*_{jn} ... d\varepsilon^*_{Jn},\ j \neq i \tag{5}$$

where $f\left(\cdot\right)$ is the probability density function of the $\left(J-1\right)$-dimensional multivariate normal distribution.

2.2.1 Two-Variate Bivariate Screening (TVBS) Approach

The likelihood function of the MNP model entails the evaluation of a $\left(J-1\right)$-dimensional integration, which can be easily evaluated using the new TVBS approach for the analytic evaluation of the MVNCD function. For $\left(J-1\right) \geq 2$, $K = Floor\left(\frac{J-1}{2}\right)$, $\frac{J-1}{2}$ is rounded down to the nearest integer to obtain K. If $\frac{J-1}{2} \cdot K = 0$, set $\bar{K} = K - 1$; else set $\bar{K} = K$. The probability of choosing mode i can be expressed as (subscript n is suppressed below):

$$P_i = P\left(\varepsilon^*_j < V^*_j\right) = P\left(\varepsilon^*_1 < V^*_1, \varepsilon^*_2 < V^*_2\right) \times \prod_{k=1}^{\bar{K}} P\left(\varepsilon^*_{2k+1} < V^*_{2k+1}, \varepsilon^*_{2k+2} < V^*_{2k+2} \mid \varepsilon^*_1 < V^*_1, \varepsilon^*_2 < V^*_2, ..., \varepsilon^*_{2k} < V^*_{2k}\right)$$

$$\approx P\left(\varepsilon^*_1 < V^*_1, \varepsilon^*_2 < V^*_2\right) \times \prod_{k=1}^{\bar{K}} P\left(\bar{\varepsilon}^*_{2k+1} < \bar{V}^*_{2k+1}, \bar{\varepsilon}^*_{2k+2} < \bar{V}^*_{2k+2} \mid \bar{\varepsilon}^*_{2k-1} < \bar{V}^*_{2k-1}, \bar{\varepsilon}^*_{2k} < \bar{V}^*_{2k}\right)$$

where $\bar{\varepsilon}^*_r = \frac{\varepsilon^*_r - E(\varepsilon^*_r)}{\sqrt{Var(\varepsilon^*_r)}}$, $\bar{V}^*_r = \frac{V^*_r - E(\varepsilon^*_r)}{\sqrt{Var(\varepsilon^*_r)}}$ (6)

The bivariate distribution $\bar{\varepsilon}^*_{2k+1}, \bar{\varepsilon}^*_{2k+2} \mid \bar{\varepsilon}^*_{2k-1}, \bar{\varepsilon}^*_{2k}$ is a bivariate skew-normal distribution rather than a bivariate normal distribution. It is assumed to be a two-variate bivariate-screened distribution (see Kim and Kim (2015)) in the TVBS approach. The corresponding conditional cumulative distribution function at each step can be expressed as a ratio of a four-variate normal cumulative distribution function (CDF) and a two-variate normal CDF. For more details about the TVBS approach, please refer to Bhat (2018).

3. DATA AND SAMPLE DESCRIPTION

The primary data for the current analysis include the commute trip data and the level-of-service (LOS) data.

3.1 Commute Trip Data

The commute trip data used in this paper were obtained from a 2017-2018 web-based travel survey of Shanghai commuters. The web-based survey was accessible to all smartphone users and internet users (see Duan et al. (2020) and Li et al. (2019)) for additional information on the survey). The survey collected detailed socioeconomic and demographic information, and a complete 24-hour travel diary reported by 2033 individuals. The detailed trip data included origin and destination locations, trip beginning and ending times, travel mode, trip purpose, and the number of companions. After data screening to remove records with missing data for the explanatory variables of interest and commute travel mode choice, the final sample comprised commute trips of 1743 commuters.

The travel modes considered in our analysis included (1) car (drive alone, car-pool, and car-sharing), (2) taxi, (3) metro, (4) bus, (5) a combination of bus and metro (hereinafter referred to as Bus & Metro), and (6) the non-motorized mode (bicycling and walking). Even if some commuters do not own private cars or bicycles, they can still use car-sharing and bike-sharing services, so they do have the car and non-motorized modes available. However, the bus, metro and Bus & Metro modes may not be available for commuters who live far away from bus stops or rail stations. Based on the maximum access/egress distance reported by individuals in the survey and the 5th Shanghai Comprehensive Transport Survey (2015), we set the cutoff threshold distance for bus availability to 2 km; that is, the bus mode is considered available only if the access/egress distance for an individual is less than 2 km. The corresponding cutoff distance for the metro was set to a distance of 5 km.

3.2 Level-of-Service (LOS) Data

The LOS characteristics of different travel modes were extracted from the zone-to-zone travel impedance matrices generated from the transportation networks of Shanghai, which were integrated into TransCAD based on the GIS data of roads (links and nodes), bus lines and stops, metro lines and stops, and the residential zone of each respondent. Travel times calculated from floating car data were added to each link of the road network (Zhang et al., 2019). Travel times, service frequencies, and fares by time of day of were appropriately appended.

3.3 Sample Description

Table 2 provides a brief summary of the socioeconomic and demographic characteristics of the sample. Men account for a little shy of half of the commute trips (45.4%). More than 80% of commuters are 20-40 years old. Most commuters are married, hold a driving license, and live with family. The majority of commuters are well educated, with a bachelor's degree (78.5%) or a graduate degree (13.6%). Personal monthly income is heavily clustered between 4.5k and 15k RMB Yuan. The average personal monthly income is 10.2k RMB Yuan. More than half (62.2%) of commuters have an available private car on the trip day. 30.3% of commuters have an available private bicycle on the trip day. These statistics are reasonably close to the statistics of all commuters in Shanghai (see the 5th Shanghai Comprehensive Transport Survey (2015)), even if slightly skewed toward women and highly educated individuals. The average population density of origin TAZs (residential areas) is slightly greater than that of destination TAZs (workplaces). And the average employment density of commuters' workplaces is greater than that of residential areas, as expected.

Descriptive statistics of LOS characteristics are shown in **Table 3**. The average trip distance for the non-motorized mode is 4.204 km, indicating the short-distance nature of commute trips that use non-motorized modes. In terms of average fare, the taxi mode has the highest fare because the Shanghai taxi has a high starting price at 14 RMB Yuan for the first 3 km. The average in-vehicle commute time for the car, taxi, and metro modes are all around 20 minutes, while the bus and Bus & Metro's in-vehicle travel times rise significantly to 37.999 and 38.747 minutes, respectively. The higher in-vehicle travel time of the bus mode is to be expected, because of the large number of stops and roundabout operating routes of Shanghai bus routes. The average initial waiting time and transfer waiting time of metro are shorter than those of bus and Bus & Metro, a reflection of the fact that the metro system provides a higher service frequency across all its many lines. In terms of average access/egress distance, bus and Bus & Metro have substantially shorter distances than those of metro because of the better spatial coverage of the service area by buses. And metro's average access distance is somewhat longer than the average egress distance, presumably due to the denser distribution of metro stations in workplaces than in residential areas. The combined Bus & Metro mode requires a slightly greater number of transfers than that of bus alone or metro alone, and the average transfer walking distance of Bus & Metro is greater than that of bus, as expected.

In terms of the commute mode shares, they are as follows: Car (34.5%), taxi (1.9%), metro (21.0%), bus (12.4%), bus and metro (4.1%), and non-motorized mode (26.1%). Compared to cities in the US, a much higher fraction of commuters use non-car modes, especially non-motorized modes.

Table 2 Sample characteristics (N=1743)

Categorical variables	Categories		Percentage (%)
Gender	Male		45.439
	Female		54.561
Age	Younger than 20 years		2.811
	21-30 years		34.079
	31-40 years		46.242
	41-50 years		13.827
	Above 50 years		3.041
Marital Status	Married		72.060
	Unmarried		27.940
Driving License	Own		75.961
	Does not own		24.039
Residential Type	Family		87.722
	Dormitory		11.819
	Other		0.459
Education Attainment	Less than high school		1.549
	High school		6.311
	Bachelor's degree		78.543
	Graduate degree		13.597
Personal Monthly Income (RMB Yuan)	Less than 2k		2.754
	2 k - 4.5 k		8.319
	4.5 k - 6 k		14.974
	6 k - 8 k		17.843
	8 k - 10 k		20.023
	10 k - 15 k		20.367
	15 k - 20 k		7.975
	20 k - 30 k		5.221
	Greater than 30 k		2.524
Private Vehicles	Car		62.192
	Electric bicycle		29.260
	Bicycle		30.293
	Motorcycle		2.008
Continuous Variables		**Mean**	**S.D.**
Personal Income [(1)](10k RMB Yuan/month)		1.018	0.638
Population Density (1000 people/km^2)	Origin TAZ	2.538	2.178
	Destination TAZ	1.252	1.855
Employment Density (1000 positions/km^2)	Origin TAZ	1.794	1.994
	Destination TAZ	2.367	2.704

[(1)] The continuous variable "Personal Income" was generated from the categorical variable "Personal Monthly Income". The exchange rate of RMB Yuan to US dollar is approximately 6.9:1

Table 3 Descriptive statistics of LOS (Level-of-Service) attributes

Mode	Attribute	Mean	S.D.
Car	Fare (RMB Yuan)	7.065	6.471
	In-vehicle time (min)	23.406	16.604
Taxi	Fare (RMB Yuan)	35.490	28.880
	In-vehicle time (min)	23.406	16.604
Metro	Fare (RMB Yuan)	3.938	0.948
	In-vehicle time (min)	20.469	14.714
	Initial waiting time (min)	2.164	0.317
	Transfer waiting time (min)	1.226	1.455
	Access distance (km)	1.826	1.127
	Egress distance (km)	1.327	0.978
	Number of transfers	0.568	0.669
Bus	Fare (RMB Yuan)	3.458	1.707
	In-vehicle time (min)	37.999	29.897
	Initial waiting time (min)	4.281	2.751
	Transfer waiting time (min)	3.152	4.501
	Transfer walking distance (km)	0.110	0.240
	Access distance (km)	0.657	0.427
	Egress distance (km)	0.638	0.430
	Number of transfers	0.729	0.854
Bus & Metro	Fare (RMB Yuan)	3.610	1.626
	Total In-vehicle time (min)	38.747	18.981
	In-vehicle time allocated to metro (min)	22.060	14.584
	In-vehicle time allocated to bus (min)	16.687	14.436
	Initial waiting time (min)	3.599	2.658
	Access distance (km)	0.720	0.441
	Egress distance (km)	0.679	0.407
	Number of transfers	0.994	1.026
	Transfer waiting time (min)	2.833	3.556
	Transfer walking distance (km)	0.126	0.258
Non-Motorized Mode	Trip distance (km)	4.204	5.611

4. EMPIRICAL RESULTS AND POLICY IMPLICATIONS

4.1 Model Goodness of Fit

We begin our presentation of the results with a comparison of the model fit of the fully flexible MNP model with those of the more traditional models (including the MNL, CNL, HI-MNP, and HONI-MNP models). Multiple goodness-of-fit measures are computed, including initial log-likelihood ($LL(0)$), the log-likelihood at convergence ($LL(\beta)$), AIC (Akaike Information Criterion, $=2*\left[\textit{number of model parameters-}LL(\beta)\right]$), BIC (Bayesian Information Criterion, $=-LL(\beta)+0.5*\textit{number of model parameters}*ln(\textit{sample size})$). The model with a higher log-likelihood and smaller AIC/BIC values is the preferred model. Further, to compare the MNL and

CNL models with the MNP model using a statistical test, a non-nested test is applied (see Ben-Akiva and Lerman (1985)). To do so, the adjusted log-likelihood ratio statistic of each model is first computed:

$$\bar{\rho}^2 = 1 - \frac{LL(\beta) - K/2}{LL(0)}$$

where K is the number of model parameters. The non-nested test statistic is

$$P\left(\bar{\rho}_1^{\,2} - \bar{\rho}_2^{\,2} > z\right) \le \Phi\left(-\sqrt{-2 \cdot LL(0) \cdot z}\right)$$

where $\Phi(\ )$ represents the CDF of standard normality and z takes a positive value. That is, the probability that $\left(\bar{\rho}_1^{\,2} - \bar{\rho}_2^{\,2} > z\right)$ could have occurred by chance is no larger than $\Phi\left(-\sqrt{-2 \cdot LL(0) \cdot z}\right)$. A small value for the non-nested test statistic indicates a small probability of erroneously selecting the incorrect model. And the model with a higher value for the adjusted likelihood statistic is preferred. The non-nested test is then used to compare the MNP model with all the other models.

In addition to the likelihood-based metrics just discussed, we also compare the data fit of the many models intuitively and informally at both disaggregate and aggregate levels. At the disaggregate level, the average probability of correct prediction is computed. At an aggregate level, the numbers of individuals predicted to choose each mode are compared to the observed numbers choosing each mode, and an absolute percentage error (APE) measure is computed at the individual mode level and then averaged across modes to obtain a mean absolute percent error (MAPE).

The disaggregate data fit measures are presented in **Table 4**. It shows that the MNP model performs best with the highest log-likelihood and the smallest AIC/BIC values. From the informal non-nested likelihood statistic values provided in **Table 4**, it can be inferred that the probability of the adjusted likelihood differences between the MNP model and the more traditional models (the MNL, CNL, HI-MNP, HONI-MNP models) occurring by chance is literally zero. The average probability of correct prediction (as shown in the last row of **Table 4**) for the MNP model is higher than those of the other four models. The probability value for the MNP model, 0.667, is about four times the probability of correct prediction based on a random choice assignment (1/6=0.167).

Table 4 Disaggregate data fit measures

Goodness-of-fit	MNL	CNL	HI-MNP	HONI-MNP	MNP
LL(β)	-1793.233	-1785.255	-1771.174	-1771.549	-1757.217
LL(0)	-2659.259	-2659.259	-2659.259	-2659.259	-2659.259
AIC	3640.467	3628.51	3604.347	3605.097	3582.434
BIC	3787.977	3786.947	3773.712	3774.462	3768.188
non-nested test	4.97E-15	5.33E-12	1.76E-06	1.55E-06	--
Average probability of correct prediction	0.570	0.592	0.629	0.618	0.667

The aggregate data fit measures are provided in **Table 5**. The MNP model again performs better than the other four models, in terms of the APE. The MAPE for all the five models is presented in the last row of **Table 5**. The MNP model outperforms the other four models, with a MAPE of over 15.6% compared to the MAPE of more than 30% for the other models.

Table 5 Aggregate data fit measures

Modes \ Models	Observed	MNL Prediction (APE)	CNL Prediction (APE)	HI-MNP Prediction (APE)	HONI-MNP Prediction (APE)	MNP Prediction (APE)
Car	602	780 (0.296)	762 (0.266)	681 (0.131)	692 (0.150)	661 (0.098)
Taxi	33	10 (0.697)	13 (0.606)	12 (0.636)	9 (0.727)	26 (0.212)
Metro	367	463 (0.262)	420 (0.144)	451 (0.229)	474 (0.292)	397 (0.082)
Bus	217	39 (0.820)	83 (0.618)	135 (0.378)	116 (0.465)	167 (0.230)
Bus & Metro	72	50 (0.306)	41 (0.431)	46 (0.361)	54 (0.250)	51 (0.292)
Non-Motorized Mode	452	401 (0.113)	424 (0.062)	418 (0.075)	398 (0.119)	441 (0.024)
MAPE		0.415	0.354	0.302	0.334	0.156

The data fit measures at both disaggregate and aggregate levels indicate that models that consider scale heterogeneity across alternatives will generally have a better performance than the homoscedastic models. As shown, the HI-MNP performs better than the MNL and the CNL, and the MNP has a better performance than the HONI-MNP. Similarly, models that consider correlation across utilities also perform better, as reflected in the superior data fit of the CNL over the MNL and the MNP over the HI-MNP. These results indicate that scale heterogeneity across alternative modes and the correlation among them should generally not be ignored *a priori*.

4.2 Model Estimation Results

4.2.1 Value of Time

The implied value of travel time (VOT) may be obtained in a straightforward manner from the coefficients on in-vehicle time and cost. These are shown in **Table 6** for the different models. The VOT from the MNP is higher than that of other models, with a value of 36.615 RMB Yuan/hour, less than the average hourly wage of the sample, 60.84 RMB Yuan/hour (The average monthly income of the sample is 10.18k RMB Yuan, and the normal working hours per year is about 2,000 hours).

Table 6 VOT of the MNL, the CNL, and alternative MNP models

Coefficients and VOT	**MNL**	**CNL**	**HI-MNP**	**HONI- MNP**	**Full MNP**
In-vehicle time (min)	-0.0413	-0.0472	-0.0262	-0.0250	-0.0119
Travel cost (RMB Yuan)	-0.0765	-0.0994	-0.0470	-0.0432	-0.0195
Value of Travel Time (RMB Yuan/hour)	32.371	28.484	33.459	34.720	36.615

4.2.2 Explanatory Variable Effects

The coefficients of the different variables in the utility function of each mode are of the same sign. So, to conserve on space, we only present the estimation results of the MNP model in **Table 7**. In the following sections, variable effects are discussed by variable category. These effects correspond to the $\boldsymbol{\beta}$ coefficient, and provide the impact of each exogenous variable on the utility of alternatives.

Effects of Level-of-service Variables

The coefficients in **Table 7** show the anticipated negative effects of in-vehicle time and travel cost for the motorized modes (car, taxi, metro, bus, Bus & Metro). Access/egress distance adversely affects the utilities of public transportation modes (metro, bus, Bus & Metro). As expected also, waiting time is viewed as being much more onerous than in-vehicle time for the public transportation modes. The waiting and transferring environment at public transit stations is crowded and uncomfortable, and commuters are usually anxious to be on their way. Finally, in the set of LOS variables, commute distance has a strong negative effect on the use of non-motorized modes.

Table 7 Estimation results of the MNP model (N=1743)

Variable	Parameter	t-statistic
Alternate specific constants (Non-motorized mode is base)		
Car	-2.6067	-6.348
Taxi	-2.4386	-3.302
Metro	1.5513	5.140
Bus	0.5754	1.820
Bus & Metro	0.7802	2.731
Level-of-service variables		
In-vehicle time (min)-Motorized modes	-0.0119	-2.572
Travel cost (RMB Yuan)-Motorized modes	-0.0195	-3.426
Access/Egress distance (km)-Public transportation modes	-0.3405	-5.373
Waiting time (min)-Public transportation modes	-0.0766	-3.924
Trip distance (km)-Non-motorized mode	-0.1116	-9.634
Commute trip characteristics		
Number of companions		
Car	0.0929	3.603
Taxi	0.1437	1.929
Bus & Metro	-0.2876	-2.491
Socio-demographic and employment variables		
Male		
Bus	-0.1355	-1.709
Married		
Car	0.2927	2.513
Living with family		
Car	0.7796	3.978
Personal monthly income (10k RMB Yuan)		
Car	0.5804	6.315
Taxi	0.7535	3.894
Metro	0.3033	2.813
Having a driving license		
Car	1.5204	6.727
Having available private cars on the trip day		
Metro	-0.7538	-3.687
Bus	-1.5805	-3.758
Having available private bikes on the trip day		
Non-motorized mode	0.8100	6.860
Workplace employment density (1k positions/km^2)		
Taxi	0.0775	2.185
Metro	0.0530	2.472
Bus	0.0397	2.083

Effects of Commute Trip Characteristics

Among the commute trip characteristics that we considered, the number of companions has a significant impact on travel mode choice. In particular, the number of companions has a positive effect on the probability of choice of taxi, a not-very-surprising result that may be attributed to lower taxi costs with a higher level of sharing (the taxi cost included as a level of service variable was for the overall cost of the trip).

Effects of Socio-demographic and Employment Attributes

In the bus utility function, a negative coefficient indicates that men are less likely to take the bus for their commute. The higher propensity to use the car mode among married commuters and those who live with their families (rather than live in dormitories) may be attributed to the convenience and privacy offered by the car during the joint travel of family members. A high income leads to a higher predisposition to use the high-quality, but also the high-cost modes of car, taxi, and metro. The magnitudes of the income coefficients for the different modes suggest a particular inclination toward the taxi mode, which seems reasonable given the taxi mode obviates the need to drive. The next variable, corresponding to "Having a driving license" increases the propensity to use the car mode (note that the car mode, in our analysis, includes driving personally, or car-pooling, or car-sharing). This effect should be viewed as an elevated propensity to use the car-pool version of the "car" mode because a person without a driving license will not have the options of driving personally and/or using car-sharing. This result of an elevated tendency to use the car-pooling mode among those with a driving license is to be expected, since car-pooling arrangements generally entail taking turns to drive. Next, as expected, the availability of a private car leads to the reduced propensity to use metro and bus modes, while the availability of a private bicycle available on the trip day intensifies the use of the bicycle as the commute mode. Finally, areas with higher employment densities have fewer parking facilities and higher parking fees. As a result, commuters working in these areas are less likely to drive (alone or with others) to work, and more likely to take a taxi, bus, or metro.

4.2.3 Error Correlation Structures and Covariance Matrices

For identification and normalization, all the elements related to the non-motorized mode were fixed in the variance-covariance matrix in the fully flexible MNP model. Error correlation structures and variance-covariance matrices of the CNL, HI-MNP, HONI-MNP and MNP models are presented in **Table 8**.

The first row panel of **Table 8** provides information regarding the implied overlapping nesting structure of the CNL model. This nesting structure is presented in **Figure 1**. Metro is involved in both nest A and B. The dissimilarity parameter of nest A is significant, with a value of 0.581 (shown in **Table 8**). It indicates that the alternatives (car, taxi, and metro) in nest A have positive correlations and substitutability. Metro has a substitutive relation with the car and taxi modes, probably because of the well-developed metro system in Shanghai (see further discussion on this issue later in this section). The allocation parameter describing the similarity of the metro mode to the car and taxi modes in nest A is 0.092 (shown in **Table 8**), while the similarity of the metro mode to the public transportation modes in nest B is much higher at 0.908). This is because metro, bus, and Bus & Metro are more closely correlated and substitutable than car, taxi, and metro, which is also in line with the correlations estimated by the HONI-MNP and the MNP in **Table 8**.

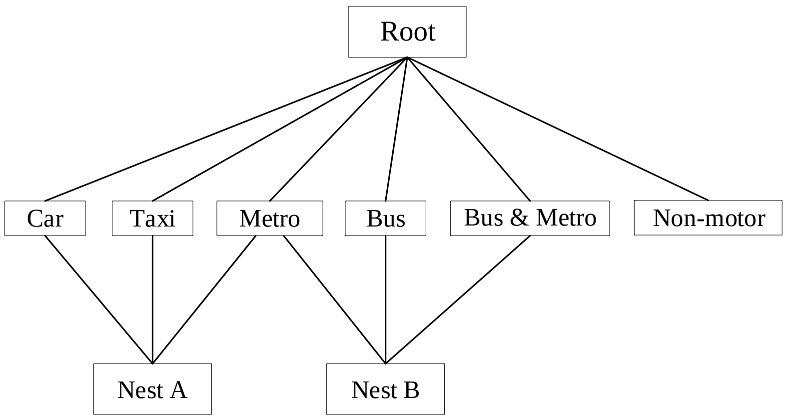

Figure 1 Nesting structure of the CNL model

Table 8 Error correlation structure and covariance matrices of the CNL and the MNP models

Models	**CNL**		**HI-MNP**		**HONI- MNP**		**Full MNP**	
	Coeff.	**T-test**	**Coeff.**	**T-test**	**Coeff.**	**T-test**	**Coeff.**	**T-test**
Error Correlation Structure								
mu(car, taxi, metro) = mu(metro, bus, Bus & Metro)	0.581	9.74	--	--	--	--	--	--
alpha for metro for the nest corresponding to (car, taxi, metro)	0.092	1.88	--	--	--	--	--	--
Variance (non-motorized mode = 1)								
Taxi	1.000	--	1.074	1.92	1.000	--	1.000	--
Car	1.000	--	0.589	3.92	1.000	--	0.887	2.35
Metro	1.000	--	**3.077**	2.55	1.000	--	**1.221**	2.83
Bus	1.000	--	**4.178**	3.61	1.000	--	**7.953**	5.70
Bus & Metro	1.000	--	1.108	3.39	1.000	--	1.189	1.05
Covariance (Correlation)								
between Car and Taxi	0.662	3.82	--	--	0.828	9.82	0.805 (0.855*)	2.35
between Car and Metro	0.200	3.26	--	--	0.265	2.24	0.470 (0.451*)	2.06
between Bus and Metro	0.631	7.47	--	--	0.624	13.41	2.128 (0.683*)	2.90
between Bus & Metro and Bus	0.662	6.94	--	--	0.516	3.06	2.049 (0.666*)	2.83

*: correlations transferred from covariance matrices

The second row panel of **Table 8** provides the variances of the alternatives. These are relevant only in the heteroscedastic but independent MNP (HI-MNP) and MNP models, because the MNL, CNL and the homoscedastic but non-independent MNP (HONI-MNP) assume a constant (and normalized) variance across all modes. The results reveal that the HI-MNP overestimates metro variance and underestimates bus variance when compared with the MNP, though both these models show a greater variance for bus than metro. This latter result indicates that unobserved variables affecting bus utility have greater variances than those affecting metro utility. For example, comfort level is an unobserved variable whose values generally vary considerably for the bus mode because there are several different kinds of bus services in Shanghai, including customized buses (or demand-response transit), bus rapid transit (BRT) and regular buses. Occupancy rates may vary among these bus services. Even regular bus service can have different occupancy rates on different routes. Some buses are equipped with air conditioners, while others are not. The metro mode, however, has little variation in comfort level. Therefore, the random component for the bus mode has a greater variance than that for the metro mode.

In terms of correlations presented in the last row panel of **Table 8**, the MNL model, of course, has no error correlation due to the IID assumption (the MNL model is not presented in **Table 8**). The HI-MNP assumes that random utilities of different travel modes are not correlated. The table indicates that the CNL, the HONI-MNP, and the MNP models all reveal positive correlations for the pairwise alternatives of car/taxi, car/metro, and bus/metro. In the context of single choice models (that is, when only one alternative can be chosen), such positive correlations imply a higher level of substitutability between the corresponding pairs of modes relative to assuming zero correlation (as in the MNL). Of the pairwise correlations, those between car/taxi and bus/metro are to be expected. Cars and taxis are characterized by their mobility and flexibility and both belong to the category of a private transportation mode. Meanwhile, bus and metro are both public transportation modes and have many aspects in common. However, the positive correlation between the car and metro modes, even though less than the positive correlations between car/taxi and bus/metro, is particularly interesting because one is a private mode while the other is a public transportation mode. This result, though perhaps likely to be unique to many Chinese cities, is probably because the Shanghai metro has been well developed and provides a convenient, high-frequency and punctual service. Shanghai metro operates on a strict schedule, making it attractive to most commuters. The Shanghai metro operates at a speed (almost 30 km/h) even faster than the speed of road traffic during peak hours. In addition, it is difficult to find a temporary parking lot during peak hours and also highly expensive to reserve a parking lot because of limited parking spaces around workplaces. This finding suggests that improvement in metro LOS can be effective in attracting commuters away from private cars to the metro and alleviate traffic congestion during peak hours.

Also to be noted from the table is that the error correlation between car and metro is underestimated quite considerably by the CNL and HONI-MNP models relative to the MNP model (specifically by 55.65% in the CNL and by 41.24% in the HONI-MNP). The implication is that we should expect an underestimation of the increase in the metro mode when car costs/times increase and an underestimation of the draw away from the car mode when the metro level of service is improved (as predicted by the CNL and HONI-MNP models relative to the MNP model), as we will confirm in the next section when examining market share changes.

4.3 Policy Implications

4.3.1 Background

The Chinese government has implemented several policies to encourage commuters to shift from private cars to high-occupancy public transportation to address the increasing traffic congestion in Shanghai. Traffic congestion-relief policies include disincentives to use private cars, improvement in public transportation level of service (LOS), and encouragement of the use of non-motorized travel modes. To reduce the use of private vehicles, the government has adopted (and is increasingly considering further adoption) such demand management measures as a car plate auction policy to control vehicle ownership, an additional toll for the use of major highways, forbidding cars with plates from other provinces using elevated roads during rush hours, and increased parking fees. Improvements in the LOS attributes of public transportation that have been implemented (and also increasingly being considered) are the designation of bus lanes, increase in the frequency of transit service, and reduction of access/egress distance (or increase in the catchment area of transit stations). Bus lanes in Shanghai have grown to 437 km in 2019 and the average operating speed has increased by 2km/h during peak hours. The metro system in the central area of Shanghai decreased its peak-hour headway to three minutes in 2018 with over 5000 metro trains. The percent of catchment area of metro stations based on 600-meter circular buffers is more than 71% within the inner-ring area in Shanghai, and that based on 500-meter circular buffers for bus stops is more than 92% within the outer-ring area in Shanghai. The number of metro stations has also been increased from 366 in 2015 to 415 in 2018, and there will be new metro lines and metro stations in the next few years (Shanghai Transport & Port Research Center, 2018). Furthermore, the government is taking strides toward making short-distance trips more convenient by providing high-quality walking paths and environment, and by implementing policies that encourage bike-sharing services. However, many of these policies have only been recently implemented (or are still being considered), and there has been little analysis of the likely effectiveness of these policies on individuals' commute mode choices. Travel mode choice models, such as the one estimated in this paper, provide an analytical tool for evaluating the impact of congestion-relief policies to encourage the shift from private cars to other modes. In this paper, we focus on three main policies: (1) highway tolls, (2) improvement in the frequency and access/egress distance of the metro system, (3) car ownership and driving license ownership. The last of these may provide insights on any regulations the government may want to impose on the purchase of cars and/or the number of driving licenses issued. Mode share changes with these different policy actions are presented in **Table 9** and discussed below.

Table 9 Market share change (%△P)

Models / Modes	MNL	CNL	HI-MNP	HONI- MNP	MNP
when the highway toll is increased by 5 Yuan					
Car	-2.123	-2.153	-1.325	-2.185	-2.073
Taxi	-2.149	-2.121	-1.470	-2.579	-2.395
Metro	1.169	0.906	0.780	1.172	1.258
Bus	0.485	1.107	0.953	1.059	1.478
Bus & Metro	0.790	1.241	0.880	1.441	0.674
Non-motorized	0.964	0.716	0.585	0.960	0.962
when the waiting time of the metro mode is decreased by 1 minute					
Car	-0.590	-0.772	-1.268	-0.588	-0.900
Taxi	-0.386	-0.218	-0.260	-0.632	-0.776
Metro	2.336	2.865	4.123	1.848	2.647
Bus	-0.412	-0.437	-1.229	-0.668	-0.944
Bus & Metro	-0.475	-0.539	-0.671	-0.161	-0.141
Non-motorized	-0.308	-0.444	-1.046	-0.353	-0.487
when access/egress distance of the metro mode is decreased by 0.1 km					
Car	-0.229	-0.330	-0.716	-0.579	-0.712
Taxi	-0.151	-0.107	-0.146	-0.622	-0.614
Metro	0.909	1.237	2.330	1.818	2.093
Bus	-0.161	-0.194	-0.694	-0.657	-0.747
Bus & Metro	-0.185	-0.231	-0.377	-0.158	-0.111
Non-motorized	-0.120	-0.191	-0.593	-0.348	-0.385
when car ownership is decreased by 1%					
Car	-0.095	-0.106	-0.201	-0.151	-0.204
Taxi	0.013	0.003	0.029	0.003	0.032
Metro	0.151	0.275	0.264	0.214	0.262
Bus	0.177	0.130	0.190	0.246	0.196
Bus & Metro	0.045	0.050	0.032	0.021	0.019
Non-motorized	0.175	0.249	0.204	0.278	0.214
when driving license ownership is decreased by 1%					
Car	-0.932	-0.944	-0.840	-0.957	-0.824
Taxi	0.025	0.004	0.087	0.004	0.083
Metro	0.295	0.316	0.204	0.241	0.212
Bus	0.220	0.133	0.233	0.104	0.229
Bus & Metro	0.083	0.092	0.042	0.021	0.021
Non-motorized	0.404	0.603	0.237	0.566	0.245

4.3.2 Impact of Highway Tolls on Commute Mode Shares

Since Shanghai highway tolls start at 5 Yuan (with 5 Yuan also being the basic unit for price changes), the percentage change in mode shares is calculated for an additional 5 Yuan toll for the private car and taxi modes. As expected, this leads to a decrease in share for the car and taxi modes, and an increase in share for the other modes, as predicted by all the five models (see the first row panel of **Table 9).** But the non-MNP models, in general, underestimate the decrease in car and taxi modes (except for the HONI-MNP, which estimates an even higher decrease in taxi share relative to the MNP model), and underestimate the increase in share for the metro and bus modes. Between the metro and bus share increases, the bus share increase is higher. Further, the underestimation of the increase in the metro share as predicted by the non-MNP models is particularly noticeable, consistent with the discussion in the previous section in this regard. Overall, the ability to shift individuals from private modes to public transportation through the use of toll-based policies is underestimated by the non-MNP models.

4.3.3 Impacts of the Frequency and Access/Egress Distance of Metro System

To analyze the impacts of frequency and access/egress distance improvements for the metro mode, we consider a waiting time reduction by 1 minute and an access/egress distance decrease by 0.1 kilometers. The resulting mode share changes are shown in the second and third row panels of **Table 9**. The results show that the metro mode share is increased by 2.647% with a 1-min reduction of the waiting time and 2.093% with a 0.1-km decrease in the access/egress distance in the full MNP model. The corresponding metro mode share increases are either lesser or of the same order from the MNL, CNL, and HONI-MNP models, but are overestimated by the HI-MNP model. The non-MNP models also generally underestimate the draw away from the car mode due to metro mode improvements, except for the HI-MNP model. This is again consistent with our expectation (discussed at the end of Section 4.2.3) of an underestimation from the CNL and HONI-MNP models of the draw away from the car mode when the metro level of service is improved.

If the highway toll policy of an increase by 5 Yuan is compared with the policies that improve the metro level of service, the former has a higher impact on decreasing the use of private cars and taxis, and the latter does better in attracting commuters to take the metro. Therefore, both kinds of measurements can work together to reduce the use of private transportation modes and increase the market share of public transportation.

4.3.4 Impacts of Car Ownership and Driving License Ownership

By 2017, there were 2.74 million private cars in Shanghai (Shanghai Municipal Statistics Bureau, 2018). The number of driving licenses issued (7.61 million) in Shanghai are at about 2.78 times the number of cars owned. With more convenient and efficient car-sharing services emerging, an increase in driving licenses is likely to correlate with an increasing car commute trips, particularly for young workers who cannot afford to own a car but hold a driving license. Here we investigate the effect of car ownership and driving license ownership on travel mode shares. Currently, as shown in **Table 2**, about 62% of sample respondents have a private vehicle available, and about 76% of respondents have a driving license. We investigate the effects of policies that contain car ownership rates and meter driving license issuance. Specifically, we examine the effect of a decrease by 1% in private car availability and a reduction in 1% of individuals holding driving licenses.

The results, presented in the last two row panels of **Table 9**, show that the changes in the non-car modes are rather low, and all positive, even as they each absorb some share of the reduction in the car mode share because of the car ownership/driving license policies. So, we will focus on the car mode share changes here. The non-MNP models underestimate the decrease in car mode share because of a car availability reduction, and overestimate the reduction in car mode share due to a driving license curtailment policy. Despite these differences, all models indicate that a license ownership restriction has a much larger effect on car mode share than does a car availability reduction policy. This does suggest an emphasis on strict driving license issuance regulations to reduce the use of private cars, while limiting car ownership can be a supplementary policy to reduce car use.

5. CONCLUSIONS AND DISCUSSIONS

The MNP model has rarely been applied for mode choice modeling, in both research and practice. This paper applied an MNP model to analyze Shanghai commute mode choice. Bhat's (2018) TVBS method, which is a matrix-based analytic approach to evaluate the MVNCD function, is employed in model estimation. The dataset was derived from a web-based travel survey of Shanghai commuters. Level of service attributes were generated from the transportation network of Shanghai. The travel modes considered in this study were car, taxi, metro, bus, Bus & Metro and non-motorized modes. In addition to the MNP model, we also estimated four other models; (1) the multinomial logit (MNL) model that assumes independent and identically distribution utility error terms across alternatives, (2) the cross-nested logit (CNL) model that relaxes the independence assumption across alternatives, but maintains identical error terms, (3) the heteroscedastic but independent MNP (HI-MNP) model that relaxes the identical error term assumption, but maintains independence, and (4) the homoscedastic but non-independent MNP (HONI-MNP) that relaxes the independence assumption but imposes homoscedasticity of error terms. Overall, from a data fit perspective at, both the disaggregate and aggregate levels, (a) the MNP clearly outperforms all the other four models, (b) the HI-MNP performs better than the MNL and the CNL models, and (c) the HONI-MNP provides a better data fit than the MNL model. Interestingly, the performance of the HI-MNP and the HONI-MNP are about the same, though quite inferior to the performance of the MNP. In totality, these results underscore the importance of considering both heteroscedasticity as well as correlated error terms when estimating mode choice models.

The variance and correlation structures from the many models provide useful insights and also have relevance for policy analysis. The models allowing for heteroscedasticity indicate a greater variance for bus than metro, suggesting much higher variability in the quality of bus-related equipment, bus stop environment, and bus service relative to the more streamlined and less variable metro rail service. Interestingly, whenever correlations were allowed in the models, these turned out to be positive. Of the pairwise correlations, those between car/taxi and bus/metro are to be expected. However, the positive correlation between the car and metro modes, even though less than the positive correlations between car/taxi and bus/metro, is particularly interesting because one is a private mode while the other is a public transportation mode. But this result, though perhaps likely to be unique to many Chinese cities, suggests that improvement in the metro level of service can be effective in attracting commuters from private cars to metro and alleviate traffic congestion during peak hours.

Policy implications are examined and discussed. Overall, the ability to shift individuals from private modes to public transportation through the use of toll-based policies is underestimated by the non-MNP models. This suggests that there would be (inappropriately) less emphasis on implementing tolling and metro service improvement policies if the non-MNP models were to be used as the basis for policy analysis. Also, our results suggest that a highway toll policy is the most effective in decreasing the market share of car and taxi modes, while a metro level of service improvement is the most effective in increasing metro share. Therefore, both tolling and metro service improvement policies should be implemented together for maximum impact in reducing the use of private transportation modes and increasing the market share of public transportation. Additionally, between policies that regulate car purchases or cut back on driving license issuance, the latter appears to be a much more effective action to contain and decrease car mode share.

From a methodological standpoint, the TVBS method makes the evaluation of the high-dimensional integral of MVNCD more efficient and provides a feasible way to apply the MNP model to city-wide travel demand forecasting. The MNP model using this matrix-based analytic method is free from the limitations of simulation-based integration in the mixed MNL model and restrictive error structures in logit-based models such as the MNL, NL, or CNL model. We believe it is time to cast aside doubts about the estimability of MNP models, while still continuing to emphasize the best systematic specifications in our choice models. We hope that the application in this paper to a six-alternative mode choice model will pave the way for future travel demand modeling analysis using a flexible MNP model structure rather than *a priori* imposing constraints on the variance-covariance matrix.

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