National Technical University of Athens
School of Civil Engineering
Department of Transportation Planning and Engineering

# DEVELOPMENT OF METHODS FOR ESTIMATING DEMAND CHANGES IN URBAN TRANSPORT SYSTEMS DUE TO CHANGES IN NETWORK CHARACTERISTICS 

Ph. D. Dissertation

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$\mathrm{M} \varepsilon \varepsilon \pi \iota \varphi \dot{\dot{\prime}} \lambda \alpha \xi \eta \eta \pi \alpha \nu \tau \dot{\varrho} \varsigma \delta \varkappa \alpha \mu \dot{\omega} \mu \alpha \tau \circ \varsigma$. All rights reserved.







 E日vıoú Meтбóßıou По入uтєХveiou.

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Anastasia Pnevmatikou,

Dedicated to the memory of my mother who made me who I am and to my father who taught me everything else, and and to my partner Nikos for his love and support.

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## $\underline{\Sigma \mathrm{YNO}} \mathrm{H}$



















 $\mu \varepsilon \mu o v \tau \dot{\varepsilon} \lambda \alpha$ Multinomial Logit, Multinomial Probit, Heteroskedastic Extreme Value $\chi \alpha \iota$

























# "Development of Methods for Estimating Demand Changes in Urban Transport Systems due to Changes in Network Characteristics" 

Anastasia M. Pnevmatikou<br>Supervisor: Matthew G. Karlaftis, Associate Professor


#### Abstract

This dissertation explores the altered travel patterns as a result of disruptions in operation of Metro (Subway) Systems. This analysis is of particular interest as Metro Systems are the backbone of every urban network and every disruption in their operation as a result of various factors may significantly affect millions of travellers as well as the life in the city. Despite the obvious interest of analysing the impacts of the disruptions in operation of Metro Systems, this phenomenon has not been investigated enough in international bibliography, probably because of the difficulty in data collection and the complicated modelling of this phenomenon. For this analysis travel data was collected related to the various alternative ways of travel for three categories of travelers: a) travelers who remain on the partly disrupted network during the disruption, b) travelers who during closure shift to alternative modes, and return to the Metro system after the line's restoration, and c) travelers who adopt an alternative mode even after the line's restoration. For this analysis we use Revealed Preference (RP) and Stated Preference (SP) techniques to explore the importance of trip and traveler characteristics and sociodemographic characteristics on travel patterns during a Metro closure. The analysis of this data was based on Multinomial Logit, Multinomial Probit and Heteroskedastic Extreme Value and resulted in the most significant parameters that affect positively or negatively the choice of mode in case of disruptions in Subway network, for each traveler category and for each data collection method used. The main themes addressed include a joint analysis of Revealed and Stated Preference data in the context of hierarchical designs (Nested Logit) so as to strengthen both data sources. Elasticities of various level-of-service variables associated to the travelling modes in the SP choice during a Metro disruption were determined for each alternative mode. Elasticities for each level-ofservice variable and for each alternative mode during a hypothetical Subway closure were developed in the Stated Preference experiment. Results indicated that characteristics of the traveler who were making the choice in emergency situations tended to be more significant predictors of travel mode choice than the characteristics of the trips themselves. This indicates that people's travel mode choices may be driven largely by fixed attributes that revolve around demographics rather than the consideration of benefits of the different modes of travel. Among the variables tested and found to significantly affect choice of mode during Subway closures are travel cost, transfer inconvenience, income, age, habit, car availability, working schedule flexibility, travel time before and during the closure, are among the variables that influence travelers' mode choice decision during Metro disruptions. The results of this dissertation can be used to assess transport planners and policy makers to adapt and implement integrated policies promoting public transport, carpooling, walking, cycling, and teleworking and aasist them in effectively planning future closures without disrupting the life in the city.


 <br>Av $\alpha \sigma \tau \alpha \sigma i \alpha$ M. Пvєข $\mu \alpha \tau \ldots о \dot{\Delta}$<br>

## ЕктетAMENH EлএHNIKH ПЕРІлнчН

## ЕІІАГЛГН






























 $\varepsilon \pi \iota \varphi \alpha \nu \varepsilon \iota \alpha x \dot{\alpha} \mu \dot{\mu} \sigma \alpha$.













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 тou Merøó.




 $\alpha \pi о \varkappa \alpha \lambda \nu \pi \tau \dot{\mu} \mu \varepsilon \nu \eta \varsigma$ (Revealed Preference) $火 \alpha \iota ~ \delta \varepsilon \delta \eta \lambda \omega \mu \dot{\varepsilon} \nu \eta \varsigma$ (Stated Preference) $\pi \varrho о \tau i \mu \eta \sigma \eta \varsigma$, $\gamma \kappa \tau \eta \nu \alpha \pi \sigma \tau i \mu \eta \sigma \eta \tau \omega \nu \pi \varrho \circ \tau \mu \dot{\eta} \sigma \varepsilon \omega \nu \tau \omega \nu \chi \varrho \eta \sigma \tau \dot{\omega} \nu$.

##  इобтท $\mu \dot{\alpha} \tau \omega \nu$ Mєт@ó





























 $\chi \varrho \dot{v} \omega \nu$ ठı $\alpha \delta \varrho \circ \mu \dot{\eta} \varsigma \varkappa \alpha \tau \dot{\alpha} 70 \%$ ( $\alpha \pi \dot{o} 31$ غ́ $\omega \varsigma 52 \lambda \varepsilon \pi \tau \dot{\alpha}$ ).





















 $\mu \varepsilon \tau \alpha x i v \eta \sigma \eta \varsigma \varkappa \alpha \tau \dot{\alpha} \tau \eta \delta \iota \dot{\alpha} \varrho x \varepsilon 1 \alpha \tau \eta \varsigma \alpha \pi \varepsilon Q \gamma i \alpha \varsigma$.

 Sovoivou (London Assembly Transport Committee, 2009). Oı $\mu \varepsilon \tau \alpha \kappa \iota \nu \circ u ́ \mu \varepsilon v o r ~ \delta \dot{\eta} \lambda \omega \sigma \alpha \nu$




















## МЕЄОДОАОГIA

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 experiment).








 $\tau \omega \nu \mu \varepsilon \tau \alpha \chi \iota \nu \circ \dot{\mu} \mu \varepsilon \nu \omega \nu$ бє $2 \pi \varepsilon \varrho \iota \pi \tau \dot{\omega} \sigma \varepsilon \varsigma:$
а) $\chi \alpha \tau \dot{\alpha} \tau \eta \delta เ \alpha \varkappa о \pi \dot{\eta} \lambda \varepsilon เ \tau o v e \gamma i \alpha \varsigma, ~ ⿲ \alpha \iota$
















 ( $\sigma \dot{\alpha} \theta \mu \varepsilon \cup \sigma \eta ~ \sigma \varepsilon ~ \tau \dot{\alpha} \varrho \varkappa \iota \nu \gamma \varkappa, ~ \varkappa о ́ \mu ь \sigma \tau \varrho о ~ \tau \alpha \xi ฺ i) . ~$











 $\varepsilon \tau \omega \dot{)}$ ).


























 о@っб $\overline{\text { évec }} \mu \varepsilon \tau \alpha \beta \circ \lambda$ ह́c.

 $\sigma \cup \mu \mu \varepsilon \tau \varepsilon i \chi \alpha \nu$ ब $\tau \eta \nu$ ह́@ $\varrho \cup v \alpha$.

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 Sheldon, 1986).







 $\pi \varrho \alpha \gamma \mu \alpha \tau \omega \dot{\eta}$ єлı $\lambda о \gamma \dot{\eta}$.

##  елıдоүढ்





 $\varepsilon \pi \iota \lambda o \gamma \dot{\eta} s$ (Choice experiment method). $\Sigma \varepsilon \alpha v \tau \dot{\eta} v \tau \eta \mu \dot{\varepsilon} \theta o \delta o$, o в@ $\omega \tau \dot{\omega} \mu \varepsilon v o s ~ \delta \eta \lambda \dot{\omega} v \varepsilon \iota ~ \kappa \dot{\alpha} \theta \varepsilon$





 аүo@д́s







 $\mu \varepsilon \tau \alpha \varphi о \varrho$ мо่ $\mu$ غ்бо.





| M $\varepsilon \tau \alpha \beta \lambda \eta \tau \dot{\varepsilon}$ ¢ | Мєтахіиクбท $\mu \varepsilon$ $\lambda \varepsilon \omega \varphi o \varrho \varepsilon$ io | Metaxivnoŋ $\mu \varepsilon$ I.X. | $\mathrm{M} \varepsilon \tau \alpha \times i \sim \eta \sigma \eta \mu \varepsilon \tau \alpha \xi i$ |
| :---: | :---: | :---: | :---: |
|  | 25 | 15 | 10 |
|  | 40 | 30 | 25 |
|  | 50 | 40 | 35 |
| Kȯбтоя $\mu \varepsilon \tau \alpha x i \nu \eta \sigma \eta ร$ (عט○ळ') | 1.20 | 3.00 | 3.00 |
|  | 1.40 | 5.00 | 7.00 |
|  | 2.00 | 8.00 | 12.00 |
|  | 10 | 8 | 3 |
|  | 13 | 15 | 5 |
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| A¢ı $\theta \mu$ ós $\mu \varepsilon \tau \varepsilon \pi \iota \beta \beta \beta \dot{\alpha} \sigma \varepsilon \omega \nu$ | 0 | 0 | 0 |
|  | 1 | 0 | 0 |
|  | 2 | 0 | 0 |
















|  |  | \हம¢оовio |  |  |  | I．X． |  |  | T $\alpha \xi_{i}$ |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | INVT | FARE | OVT | TRA | INVT | COST | OVT | TIME | FARE | OVT |
|  | 1 | 25 | 1.2 | 10 | 0 | 15 | 3 | 8 | 10 | 3 | 3 |
|  | 2 | 40 | 1.4 | 13 | 1 | 30 | 5 | 15 | 25 | 3 | 3 |
|  | 3 | 50 | 2 | 18 | 2 | 45 | 8 | 20 | 35 | 3 | 3 |
| $\checkmark$ | 4 | 50 | 2 | 18 | 1 | 30 | 5 | 8 | 10 | 7 | 5 |
| $\begin{aligned} & \text { x } \\ & \hline 0 \end{aligned}$ | 5 | 25 | 1.2 | 10 | 2 | 45 | 8 | 15 | 25 | 7 | 5 |
| ¢ | 6 | 40 | 1.4 | 13 | 0 | 15 | 3 | 20 | 35 | 7 | 5 |
|  | 7 | 40 | 1.4 | 13 | 2 | 45 | 8 | 8 | 10 | 12 | 7 |
|  | 8 | 50 | 2 | 18 | 0 | 15 | 3 | 15 | 25 | 12 | 7 |
|  | 9 | 25 | 1.2 | 10 | 1 | 30 | 5 | 20 | 35 | 12 | 7 |
|  | 10 | 50 | 1.4 | 10 | 2 | 30 | 3 | 20 | 10 | 12 | 5 |
|  | 11 | 25 | 2 | 13 | 0 | 45 | 5 | 8 | 25 | 12 | 5 |
|  | 12 | 40 | 1.2 | 18 | 1 | 15 | 8 | 15 | 35 | 12 | 5 |
| $N$ | 13 | 40 | 1.2 | 18 | 0 | 45 | 5 | 20 | 10 | 3 | 7 |
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|  | 17 | 40 | 1.2 | 18 | 2 | 30 | 3 | 8 | 25 | 7 | 3 |
|  | 18 | 50 | 1.4 | 10 | 0 | 45 | 5 | 15 | 35 | 7 | 3 |
|  | 19 | 40 | 2 | 10 | 1 | 45 | 3 | 15 | 10 | 7 | 7 |
|  | 20 | 50 | 1.2 | 13 | 2 | 15 | 5 | 20 | 25 | 7 | 7 |
|  | 21 | 25 | 1.4 | 18 | 0 | 30 | 8 | 8 | 35 | 7 | 7 |
| $\cdots$ | 22 | 25 | 1.4 | 18 | 2 | 15 | 5 | 15 | 10 | 12 | 3 |
| 嫘 | 23 | 40 | 2 | 10 | 0 | 30 | 8 | 20 | 25 | 12 | 3 |
| ¢ | 24 | 50 | 1.2 | 13 | 1 | 45 | 3 | 8 | 35 | 12 | 3 |
|  | 25 | 50 | 1.2 | 13 | 0 | 30 | 8 | 15 | 10 | 3 | 5 |
|  | 26 | 25 | 1.4 | 18 | 1 | 45 | 3 | 20 | 25 | 3 | 5 |
|  | 27 | 40 | 2 | 10 | 2 | 15 | 5 | 8 | 35 | 3 | 5 |









 $\left.\tau \alpha \xi_{i}\right)$.


 кoוvoú $\tau \eta \varsigma$ A $\theta \dot{\eta} v \alpha \varsigma ~ \sigma \chi \varepsilon \tau \tau \dot{\alpha} \mu \varepsilon \tau \eta \lambda \varepsilon \iota \tau o v \varrho \gamma i \alpha \tau \omega \nu$ MMM.










## ANAAYロH DIAKPITRN EПIAOГתN

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 $\sigma \tau \alpha \tau \iota \sigma \tau \varkappa \dot{\omega} v \varepsilon \varphi \alpha \varrho \mu о \gamma \dot{\omega} \nu(B e n-A k i v a$ and Lerman, 1985).


 $\dot{\alpha} \lambda \lambda \eta \varsigma \varepsilon v \alpha \lambda \lambda \alpha \varkappa \tau \omega \dot{\eta} \varsigma$,
 $\varepsilon v \alpha \lambda \lambda \alpha x \tau \varkappa \varepsilon ่ \varsigma \varepsilon \pi i \lambda \alpha \gamma \dot{\varepsilon} \varsigma, \nsim \alpha \iota$



 $\tau \eta \nu \varepsilon \nu \alpha \lambda \lambda \alpha \kappa \tau \pi \dot{\eta} i \alpha \nu \alpha \pi \alpha \varrho i \sigma \tau \alpha \tau \alpha \iota \alpha \pi o ́:$

 $\tau \operatorname{\tau ov} \alpha v \alpha \lambda \nu \tau \dot{\eta}, \kappa \alpha \iota$

 $\varkappa_{\alpha \iota} \pi \alpha \varrho \alpha \tau \dot{\eta} \varrho \eta \sigma \eta s$ тou $\alpha \nu \alpha \lambda \cup \tau \dot{\eta}$.


$P_{i n}=P\left(V_{i n}+\varepsilon_{i n}>V_{j n}+\varepsilon_{j n}\right)=P\left(\varepsilon_{j n}-\varepsilon_{i n}<V_{i n}-V_{j n}\right), \forall i, j \in C_{n}$, and $i \neq j$
 T $\alpha \nu \tau о \sigma \eta \mu i \alpha \varsigma ~ \tau \omega \nu ~ \varkappa \alpha \tau \alpha \nu o \mu \dot{\omega} \nu \tau \omega \nu ~ \sigma \varphi \alpha \lambda \mu \dot{\alpha} \tau \omega \nu \tau \omega \nu \sigma \nu \nu \varrho \tau \dot{\eta} \sigma \varepsilon \omega \nu ~ \omega \varphi \dot{̇} \lambda \varepsilon ı \alpha \varsigma$ (Ben-Akiva, Lerman, 1985), $\dot{\eta}$ тo:

- $\sigma \tau \eta \nu \alpha \varrho \chi \dot{\eta} \tau \eta \varsigma ~ \alpha \nu \varepsilon \xi \alpha \varrho \tau \eta \sigma i \alpha \varsigma ~ \tau \omega \nu \quad \varkappa \alpha \tau \alpha \nu \circ \mu \dot{\omega} \nu \tau \omega \nu \sigma \varphi \alpha \lambda \mu \dot{\alpha} \tau \omega \nu \tau \omega \nu \quad \sigma \nu \nu \propto \varrho \dot{\eta} \sigma \varepsilon \omega \nu$ $\omega \varphi \dot{\lambda} \lambda \varepsilon ı \alpha \varsigma$ (Independence of Irrelevant Alternatives) $\chi \alpha \iota$

 $i \delta i \alpha \mu \varepsilon \tau \alpha \beta \lambda \eta \tau \dot{\tau} \tau \eta \tau \alpha)$ (Independent and Indentically Distributed)








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 тоv $\mu \varepsilon \tau \alpha \varkappa \iota \nu \circ \dot{\mu} \mu \vee \vee$ n:

$$
P_{n}(i)=\frac{e^{\mu V_{i n}}}{\sum_{j=1}^{I} e^{\mu V_{j n}}}, \quad j=1, \ldots ., i, \ldots, I \in C_{n} \forall i \neq j
$$








$L L=\sum_{n=1}^{N}\left(\sum_{i=1}^{I} \delta_{i n}\left[V_{i n}-\ln \sum_{\forall I} \exp \left(V_{i n}\right)\right]\right)$

 $\sigma u v \tau \varepsilon \lambda \varepsilon \sigma \tau \eta ่ \varsigma ~ \pi \varrho о \sigma \delta \iota \circ \varrho \iota \sigma \mu \circ \dot{R} \mathrm{R}^{2}$.



$$
P_{1}=\frac{\exp \left(V_{1}\right)}{\exp \left(V_{1}\right)+\exp \left(V_{2}\right)}
$$

## Eı $\sigma \alpha \gamma \omega \gamma \dot{\eta} \sigma \tau o \pi o \lambda \omega \omega \nu \cup \mu \iota x \dot{\alpha} \mu о \nu \tau \dot{\lambda} \lambda o$ Probit









$$
\begin{gathered}
P_{n i}=P\left(V_{n i}+\varepsilon_{n i}>\mid V_{n j}+\varepsilon_{n j} \forall j \neq i\right) \mid= \\
\int_{\varepsilon_{n}} I\left(V_{n i}+\varepsilon_{n i}>V_{n j}+\varepsilon_{n j}<\forall j\right. \\
\neq i) \varphi\left(\varepsilon_{n}\right) d_{n}
\end{gathered}
$$

 $\varkappa \alpha \tau \alpha \nu \circ \mu \dot{\eta} \varsigma \pi \varepsilon \varrho \iota \varrho \varrho \dot{\alpha} \varphi \varepsilon \tau \alpha \iota \alpha \pi \dot{o} \tau \eta$ $\sigma \chi \varepsilon \dot{\sigma \eta: ~}$
$\varphi\left(\varepsilon_{n}\right)=\frac{1}{\sqrt{2 \pi} \sqrt{\left|\Sigma_{n}\right|}} \exp ^{-\frac{1}{2} \varepsilon_{n}^{\prime} \sum_{n}^{-1} \varepsilon_{n}}$

## Eı $\sigma \alpha \gamma \omega \gamma \dot{\eta} \sigma \tau o$ Heteroskedastic Extreme Value $\mu o v \tau \dot{\varepsilon} \lambda o$


 Heteroskedastic Extreme Value $\chi \alpha \iota \alpha \pi о \tau \varepsilon \lambda \varepsilon i \mu \iota \alpha \alpha \pi \lambda о \pi о \imath \eta \mu \dot{\varepsilon} \nu \eta \mu о \varrho \dot{\eta} \tau \omega \nu$ Подט $\mu \nu \nu \mu \iota x \dot{\omega} \nu$










##  


















##  $x \alpha \tau \dot{\alpha} \tau \eta \nu 5 \mu \eta \nu \eta \delta$ б $\alpha x$ ол $\dot{\eta} \lambda \varepsilon \tau \tau 00 \varrho \gamma i \alpha s$






 $\mu \alpha \zeta i \mu \varepsilon \tau \eta \nu \alpha \nu \tau i \sigma \tau o \iota \chi \eta \pi \iota \theta \alpha \nu \dot{\sigma} \tau \eta \tau \alpha \sigma \varphi \dot{\alpha} \lambda \mu \alpha \tau O \varsigma$ (p-value), $\tau \eta \varsigma$ олоi $\alpha \varsigma \eta \tau \iota \dot{\eta}$ $\varepsilon \lambda \dot{\varepsilon} \gamma \chi \varepsilon \tau \alpha \iota \alpha \nu$

 $\alpha \pi 0 \varrho \varrho i \pi \tau \varepsilon \tau \alpha \iota \sigma \varepsilon \varepsilon \pi i \pi \varepsilon \delta$ о $\sigma \eta \alpha \nu \tau \iota x \dot{\tau} \tau \eta \tau \alpha \varsigma 1 \%(5 \% \dot{\eta} 10 \%)$.

|  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| Binary Logit |  |  |  |  |
|  | K $\alpha \tau \eta \gamma o @ i \alpha$ ( $\psi \varepsilon \cup \delta о \mu \varepsilon \tau \alpha \beta \lambda \eta \tau \dot{\eta})$ | O@ıахв̇ร <br> Елıס○х்бєı与 | p-value | $T ı \mu \dot{n}$ <br> b/st.er |
| Suvin $\theta$ ŋs ¢@óvos | 20-39 $\lambda \varepsilon \pi \tau \dot{\alpha}$ | -0.114 | . 044 | -2.015 |
|  | 40-59 $\lambda \varepsilon \pi \tau \dot{\alpha}$ | -0.161 | . 007 | -2.714 |
|  | $>60 \lambda \varepsilon \pi \tau \dot{\alpha}$ | -0.261 | . 000 | -3.539 |
| А@өrós | 1 | 0.504 | . 000 | 16.516 |
| $\mu \varepsilon \tau \varepsilon \pi \iota \beta \beta \dot{\alpha} \sigma \varepsilon \omega \nu$ | 2 | 0.588 | . 000 | 25.689 |
| $x \alpha \tau \dot{\alpha}$ тท $\delta 1 \alpha x \circ \pi \dot{\eta}$ | $>=3$ | 0.405 | . 000 | 16.159 |
| इxото́s $\mu \varepsilon \tau \alpha$ кivךбŋऽ | Eथлаiठє৩бך | . 0876 | . 050 | 1.960 |
|  |  | -0.047 | . $531 \mathrm{n} / \mathrm{s}$ | -0.627 |
|  |  |  | 1117 |  |
| Log-likelihood |  |  | -454.976 |  |
| McFadden Pseudo R ${ }^{2}$ |  |  | 0.402 |  |
|  |  | тı่̇тทัas |  |  |









 $\lambda$ дıтoveүias.









##  $\pi \varrho о \sigma \omega \pi \iota х о \dot{~}$
















| Movtė̇ı | Logit ${ }^{\text {a }}$ |  | Probit ${ }^{\text {a }}$ |  | $\mathrm{HEV}^{\text {a }}$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | coefficient | t－stat | coefficient | t－stat | coefficient | t－stat |
| ＾єш甲о＠ءіо |  |  |  |  |  |  |
| $\sum \tau \alpha \theta \varepsilon \varrho \dot{\alpha} \lambda \varepsilon \omega \varphi$ ¢o＠siou | 0.959 | 3.47 | 0.66 | 3.62 | 1.011 | 3.47 |
| Нлıхіх：18－35 | n／ |  | $\mathrm{n} / \mathrm{s}$ |  | －0．419 | －1．685 |
| Нльхіх：35－45 | n／ |  | $\mathrm{n} / \mathrm{s}$ |  | －0．566 | －2．20 |
| Eıбóठ $\eta \mu \alpha$ ：$\ \Psi \eta \lambda \lambda \dot{o}$ | －0．289 | $-2.79$ | －0．207 | －2．92 | －0．347 | －2．30 |
| Eıоós $\eta \mu \alpha: \mathrm{X} \alpha \mu \eta \lambda \dot{\circ}$ | n／ |  | $\mathrm{n} / \mathrm{s}$ |  | 0.249 | 2.06 |
| Suvin $\theta \eta$ ¢ хо́vos $\tau \alpha \xi: 46-60$ | 0.276 | 2.57 | 0.205 | 2.74 | 0.348 | 2.87 |
| इuvin $\theta \eta$ ¢ Х＠óvos $\tau \alpha \xi:>=60$ | 0.766 | 5.89 | 0.527 | 5.80 | 0.885 | 6.09 |
| X＠ウ் $\eta \mu \varepsilon \tau \varrho \dot{o}>1$ بо＠$\dot{\alpha}$ 七ท $\beta \delta о \mu \dot{\alpha} \delta \alpha$ |  |  |  |  |  |  |
| I．X． |  |  |  |  |  |  |
| $\Sigma \tau \alpha \theta \varepsilon @ \dot{\alpha}$ I．X． | 1.419 | 5.00 | 0.947 | 4.45 | 1.327 | 3.77 |
| Фن̇入o：$\dot{\alpha} \mathrm{V}$ ¢ $\propto$ ¢ | 0.216 | 2.88 | 0.172 | 3.15 | 0.269 | 2.99 |
| Нлехіх：18－35 | 0.713 | 2.74 | 0.665 | 3.48 | 0.978 | 3.03 |
| Нлıхіх：35－45 | 0.573 | 2.16 | 0.566 | 2.90 | 0.789 | 2.41 |
| Нлıхіх：45－55 | $\mathrm{n} / \mathrm{s}$ |  | 0.496 | 2.43 | $\mathrm{n} / \mathrm{s}$ |  |
|  | －0．239 | －2．12 | －0．194 | －2．40 | －0．263 | －1．99 |
|  | －0．497 | －5．62 | －0．423 | －6．39 | －0．696 | －6．08 |
|  | $\mathrm{n} / \mathrm{s}$ |  | －0．116 | －2．02 | $\mathrm{n} / \mathrm{s}$ |  |
| X＠óvos evtós oxṅuatos | －0．041 | －25．34 | －0．032 | －19．94 | －0．052 | －14．84 |
|  | －0．220 | －25．55 | －0．158 | －23．38 | －0．257 | －20．14 |
|  | －0．041 | －9．44 | －0．034 | －9．52 | －0．055 | －8．36 |
|  | －0．255 | －8．08 | －0．199 | －7．62 | －0．315 | －6．91 |
| П $\propto \dot{\alpha} \mu \varepsilon \tau \varrho \circ \varsigma ~ r \lambda i \mu \alpha x \alpha \varsigma \tau \eta \varsigma ~ H E V$ $\chi \alpha \tau \alpha \nu \circ \mu \dot{\eta} \varsigma-\lambda \varepsilon \omega \varphi о \varrho \varepsilon i \alpha$ |  |  |  |  | －0．169 | －2．221 |
| Па＠$\dot{\alpha} \mu \tau \varrho \circ \varsigma ~ \varkappa \lambda i \mu \alpha x \alpha \varsigma ~ \tau \eta \varsigma ~ H E V ~$ $\chi \alpha \tau \alpha \nu о \mu \dot{\eta} \varsigma-$ I．X． |  |  |  |  | －0．343 | －6．679 |
| A＠ı $\theta \mu$ ós $\pi \alpha \varrho \alpha \tau \eta \varrho \eta \dot{\sigma \varepsilon \omega \nu}$ | 7749 |  | 7749 |  | 7749 |  |
| Null Log－Likelihood | －7829．10 |  | －7829．10 |  | －7829．10 |  |
| Final log－likelihood | －6537．45 |  | $-6531.71$ |  | －6526．57 |  |
| Likelihood ratio test | $-2583.31$ |  | $-2594.78$ |  | $-2605.06$ |  |
| Rho－square（＠2） | 0.165 |  | 0.233 |  | $0.233$ |  |




Пivax＜ऽ 5 П $\lambda \dot{\eta} \varrho \varepsilon \varsigma ~ M o v \tau \dot{̇} \lambda o$ MNL，MNP and HEV（ $\chi \varrho \dot{\eta} \sigma \tau \varepsilon \varsigma ~ \chi \omega \varrho i \varsigma ~ I . X)$.

| Movtė̇o | Logit ${ }^{\text {a }}$ |  | Probit ${ }^{\text {a }}$ |  | HEV ${ }^{\text {a }}$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Ave $\dot{\alpha}^{\alpha} \varrho \tau \eta \tau \eta$ M $\varepsilon \tau \alpha \beta \lambda \eta \tau \dot{\eta}$ | coefficient | t－stat | coefficient | t－stat | coefficient | t－stat |
| \єш甲o＠sio |  |  |  |  |  |  |
| $\Sigma_{\tau} \tau \theta \varepsilon \varrho \dot{\alpha} \lambda \varepsilon \omega \varphi$ ¢＠siou | 0.787 | 2.52 | 0.559 | 2.62 | 0.816 | 3.33 |
| Фن่入o：$\dot{\alpha} \mathrm{v}$ ¢ $\rho$ ¢ | 0.391 | 7.57 | 0.323 | 7.48 | 0.335 | 7.09 |
| Н入ıxiк：18－35 | －0．693 | －2．34 | －0．504 | －2．40 | －0．611 | －2．60 |
| Нлехіх：35－45 | －0．711 | －2．34 | －0．493 | －2．24 | －0．640 | －2．64 |
| Нлехіх：45－55 | －0．878 | －2．55 | －0．638 | －2．50 | －0．777 | －2．84 |
|  | －0．460 | －3．36 | －0．383 | －3．58 | －0．372 | －3．48 |
| Eıбós $\eta \mu \alpha$ ： $\mathrm{X} \alpha \mu \eta \lambda \dot{\circ}$ | 0.526 | 8.20 | 0.453 | 8.60 | 0.421 | 7.27 |
| Sovin $\theta \eta$ ŋ ¢＠óvos $\tau \alpha \xi$ ：46－60＇ | 0.149 | 2.16 | 0.122 | 2.08 | 0.131 | 2.18 |
|  | 0.194 | 2.48 | 0.150 | 2.32 | 0.182 | 2.71 |
|  | －0．039 | －20．99 | －0．032 | －20．88 | －0．034 | －17．30 |
| Kȯбто¢ $\mu \varepsilon \tau \alpha x i \nu \eta \sigma \eta$ ¢ | －0．299 | －37．90 | －0．245 | －41．46 | －0．271 | －23．62 |
|  | －0．039 | －5．36 | －0．032 | －5．39 | －0．032 | －5．08 |
| A＠ı $\theta \mu \dot{\rho} \varsigma \mu \varepsilon \tau \varepsilon \tau \curlywedge \beta \iota \beta \dot{\alpha} \sigma \varepsilon \omega \nu$ | －0．193 | －6．29 | －0．161 | －6．31 | －0．154 | －5．501 |
|  |  |  |  |  | 97 |  |
| Null Log－likelihood | －60971 |  | －6097 |  | －609 |  |
| Log－likelihood | －4891 |  | －489 |  | －4886 |  |
| Likelihood ratio test | －241 |  |  |  | －2420 |  |
| Rho－square（ $\varrho^{2}$ ） |  |  |  |  | 0.2 |  |







|  | X¢ท் $\tau \tau$ ¢ $\mu$ ع I．X． |  |  | X＠ウ்бтөऽ $\chi \omega \varrho$ i¢ I．X． |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | MNL | MNP | HEV | Logit | Probi | HEV |
|  | －0．929 | －0．953 | －1．010 | －0．502 | －0．496 | －0．546 |
|  | －0．709 | －0．671 | －0．670 | N／A | N／A | N／A |
|  | －0．787 | －1．117 | $-1.180$ | －0．630 | －0．697 | －0．600 |
|  | －0．199 | －0．182 | －0．200 | －0．145 | －0．139 | －0．164 |
|  | －0．690 | －0．596 | －0．590 | N／A | N／A | N／A |
|  | －1．380 | －1．900 | －1．950 | －1．661 | －1．830 | －1．637 |
| $\varepsilon_{\mathrm{D}, ~ \lambda \varepsilon \omega \varphi \rho \varrho \varepsilon i o v ~ \omega \varsigma ~ \pi \varrho o \varsigma ~ \tau о ~ \chi \varrho o ́ v o ~}^{\beta \alpha \delta i \sigma \mu \alpha \tau o \varsigma ~ \varkappa \alpha \iota}$ Х＠óvo аv $\mu \mu$ vís | －0．330 | －0．362 | －0．38 | －0．168 | －0．161 | －0．175 |
|  | －0．321 | －0．326 | －0．320 | N／A | N／A | N／A |
|  | －0．169 | －0．257 | －0．260 | －0．131 | －0．138 | －0．124 |
|  <br>  | －0．157 | －0．165 | －0．170 | －0．063 | －0．063 | －0．064 |






 $\mu \varepsilon \tau \varepsilon \pi \iota \beta \beta \dot{\alpha} \sigma \varepsilon \omega \nu$

 охŋ் $\mu \alpha \tau о \varsigma$.

## 


















 $\sigma \chi \eta \mu \alpha \tau \varkappa \dot{\alpha} \sigma \tau \eta \nu$ Eıxóv 3 .






 $\delta \varepsilon i \gamma \mu \alpha \tau o \varsigma$.


| M $\varepsilon \tau \alpha \beta \lambda \eta \tau \varepsilon{ }^{\prime}$ | Joint RP-SP |  | Joint RP-SP NL RU1 FORM |  |
| :---: | :---: | :---: | :---: | :---: |
|  | MNL |  |  |  |
|  | Parameters | t-stat. | Parameters | t-stat. |
| $\overline{\Sigma \tau \alpha 0 \varepsilon \varrho \varepsilon ̇ \varsigma}$ |  |  |  |  |
| I.X. (RP,SP) | 1.095 | 16.153 | 1.602 | 4.808 |
| $\Lambda \varepsilon \omega \varphi$ ¢овio (SP,RP) (CO, NCO) | 0.841 | 12.712 | 1.403 | 10.812 |
| T $\alpha \xi_{1}(\mathrm{RP})$ | 0.169 | 1.290 | 1.834 | 3.581 |
| Мєт@ó (xатทүо@i $\alpha \beta \dot{\alpha} \sigma \eta$ ) | - | - | - | - |
|  |  |  |  |  |
| X@óvos $\delta 1 \alpha \delta \varrho о \mu \dot{\eta} s(\pi \dot{O} \varrho \tau \alpha-\pi \dot{\rho} ¢ \tau \alpha))(\mathrm{RP})$ | 0.013 | 4.830 | 0.001 | $0.435^{\mathrm{n} / \mathrm{s}}$ |
|  | -0.040 | -34.533 | -0.098 | -5.907 |
|  | -0.039 | -10.628 | -0.104 | -5.781 |
| A¢ı $\theta \mu \dot{\rho} \varsigma \mu \varepsilon \tau \varepsilon \pi \iota \beta \iota \beta \dot{\alpha} \sigma \varepsilon \omega \nu$ (RP,SP) | -0.247 | 11.832 | -0.381 | -6.923 |
|  | -0.254 | -45.671 | -0.668 | -5.944 |
|  |  |  |  |  |
|  |  |  |  |  |
| \єш甲о@єio (CO) | 0.193 | 3.324 | 0.737 | 3.672 |
| \єம¢о@вio (NCO) | 0.115 | 2.123 | 0.983 | 4.006 |
|  |  |  |  |  |
| I.X. (SP) | 0.349 | 5.015 | 0.646 | 2.940 |
| $\overline{\mathrm{H} \lambda \iota x i \alpha ~ 35-45 ~(S P)}$ |  |  |  |  |
| \єь५о@sio - CO | -0.231 | -3.140 | -0.189 | -1.092 |
| \єш甲o@sio -NCO | -0.067 | -0.719 | 0.022 | 0.105 $\mathrm{n} / \mathrm{s}$ |

## $\overline{\Sigma \varkappa o \pi o ́ \varsigma ~ \tau \alpha \xi \iota \delta \iota o u ́: ~} £ \varrho \gamma \alpha \sigma i \alpha$

| $\Lambda \varepsilon \omega \varphi 0 \varrho \varepsilon i o-\mathrm{CO}$ (RP,SP) | 0.012 | 0.196 | -0.195 | -1.231 |
| :---: | :---: | :---: | :---: | :---: |
| I.X. (RP,SP) | -0.102 | -1.465 | -0.512 | -2.743 |
| $\Lambda \varepsilon \omega \varphi 0 \varrho$ ¢io- NCO (SP) | -0.371 | -6.573 | -. 276 | -2.022 |
| Mعт@ó (RP,SP) | -1.174 | -6.782 | -1.118 | -4.625 |
|  |  |  |  |  |
| I.X. (SP) | 0.446 | 8.443 | 0.737 | 3.924 |


I.X. (SP)
-0.102
-1.465
$-0.302 \quad-1.774$
$\Pi \alpha \varrho \alpha \mu \varepsilon \tau \varrho о t \varkappa \lambda i \mu \alpha x \alpha \varsigma$ (IV)

| RP | 1.000 | $\sum \tau \alpha \theta \varepsilon \varrho \dot{\eta}$ |
| :--- | :---: | :---: |
| SPBS | 0.426 | 5.198 |
| SPCR | 0.309 | 6.314 |
| SPTX | 0.445 | 5.890 |
| SPNBS | 0.477 | 5.481 |
| SPNTX | 0.423 | 6.081 |


| Tvлıxท่ $\alpha \pi \dot{o} x \lambda \iota \sigma \eta$ |  |  |
| :---: | :---: | :---: |
| RP | 1.283 | $\Sigma \tau \alpha \theta \varepsilon Q \dot{\eta}$ |
| SPBS | 3.010 | 5.198 |
| SPCR | 4.151 | 6.314 |
| SPNBS | 2.685 | 5.481 |
| SPNTX | 3.029 | 6.081 |


| A@ı日 $\boldsymbol{\mu} \boldsymbol{\rho}$ s $\pi \alpha \varrho \alpha \tau \eta \varrho \dot{\eta} \sigma \varepsilon \omega \nu$ |  | 18534 |
| :--- | :---: | :---: |
| LOGL | -12789.55 | -12591.14 |
| LOGL(c) | -14897.30 |  |
| Rho-square $\left(\varrho^{2}\right)$ | 0.637 |  |









 $\mu \varepsilon \tau \varrho \dot{\text { б }}$

## $\Sigma \Upsilon М П Е Р А \Sigma М А Т А ~$










 $\pi \varrho \alpha \gamma \mu \alpha \tau о \pi о \stackrel{\eta}{\theta} \eta \not \varkappa \varepsilon$ бє $3 \sigma \tau \alpha \delta \iota \alpha$.

















 $-0,5$.





























 $\pi \varrho о \eta \gamma о \cup \dot{\mu \varepsilon \nu \eta \varsigma ~ \varepsilon \mu \pi \varepsilon \iota \varrho i \alpha \varsigma, ~ \pi о \cup ~ \pi \varrho \varepsilon ̇ \pi \varepsilon \iota ~ \nu \alpha ~ \varepsilon \lambda \varepsilon ́ \gamma \chi \chi \varepsilon \tau \alpha \iota . ~}$
 $\delta \iota \alpha x \circ \pi \dot{\eta} \varsigma \lambda \varepsilon \iota \tau o v \varrho \gamma i \alpha s$.
 $\gamma \iota \alpha \tau \eta \mu \varepsilon \tau \alpha x i v \eta \sigma \dot{\eta} \tau O \cup \varsigma$ x $\alpha \tau \dot{\alpha} \tau \eta \delta \iota \dot{\alpha} \varrho x \varepsilon \iota \alpha$ тоט $x \lambda \varepsilon \iota \sigma i \mu \alpha \tau о \varsigma$
 $\alpha \pi o ́ ~ \tau \iota \varsigma ~ \mu \varepsilon \theta \dot{\delta} \delta o \cup \varsigma ~ \delta \varepsilon \delta \eta \lambda \omega \mu \dot{v} v \eta \varsigma ~ \pi \varrho о \tau i \mu \eta \sigma \eta \varsigma ~ \varepsilon i v \alpha \iota ~ \cup \Psi \eta \lambda o ́ \tau \varepsilon \varrho \varepsilon \varsigma ~ \sigma \varepsilon ~ \sigma \chi \varepsilon ̇ \sigma \eta \mu \varepsilon \tau \eta ~ \delta \iota \varepsilon \theta \nu \dot{\eta}$
 $x \alpha \iota ~ \sigma \tau \eta \nu \alpha \delta u v \alpha \mu i \alpha \tau \omega \nu \chi \varrho \eta \sigma \tau \dot{\omega} \nu \nu \alpha$ єx $\tau \mu \dot{\eta} \sigma о \nu \nu$ о@ $\theta \dot{\alpha} \tau \alpha \pi \varrho \alpha \gamma \mu \alpha \tau \iota \dot{\alpha} \chi \alpha \varrho \alpha x \tau \eta \varrho \iota \sigma \tau \iota \dot{\alpha}$





 $\sigma u v \delta \nu \alpha \sigma \tau \omega \dot{\eta} \chi \varrho \dot{\eta} \sigma \eta \tau \omega \nu \mu \varepsilon \theta \dot{\delta} \delta \omega \nu \alpha \pi \sigma \alpha \alpha \lambda \nu \pi \tau \dot{\partial} \mu \varepsilon \nu \eta \varsigma / \delta \varepsilon \delta \eta \lambda \omega \mu \dot{\varepsilon} \nu \eta \varsigma \pi \varrho о \tau i \mu \eta \sigma \eta \varsigma$.

## KPITIKH АЕIOЛОГНГН - ПРОТАГЕIГ ГIA ПЕРАITEP $\Omega$ EPEイNA

 $\gamma \iota \alpha \tau \eta \nu \pi \varepsilon \varrho \iota \varrho \alpha \varphi \dot{\eta} \tau \omega \nu \varepsilon \nu \alpha \lambda \lambda \alpha x \tau \ldots \dot{\omega} \nu \varepsilon \pi \iota \lambda \sigma \gamma \dot{\omega} \nu \tau 0 \cup \pi \varepsilon \varrho \varrho \dot{\alpha} \mu \alpha \tau O \varsigma \tau \eta \varsigma \delta \varepsilon \delta \eta \lambda \omega \mu \varepsilon \dot{\nu} \eta \varsigma, \chi \omega \varrho i \varsigma \nu \alpha$












































 $\pi \circ \cup \tau!\varsigma \pi \varrho O x \dot{\alpha} \lambda \varepsilon \sigma \varepsilon$.

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## Abbreviations

The abbreviations found below are used throughout this dissertation. They are presented by their full name when they are first used but will later on be referred to by their acronym. In the list below the acronyms are presented in alphabetical order.

| Abbreviation | Full Name |
| :--- | :--- |
| AVC | Asymptotic Variance-Covariance Matrix |
| CO | Car Owners |
| GEV | Generalised Extreme Value |
| HEV | Independence from Irrelevant Alternatives |
| IIA | In-Vepencle Time |
| IID | Intelligent Transport Systems and Identically Distributed |
| INVT | Log Likelihood |
| ITS | Maximum Likelihood Estimation |
| LL | Multinomial Logit Model Ratio Test |
| LRT | Parking Search Time |
| MLE | Multinomial Probit Model |
| MNL | Car Non-Owners |
| MNP | NCO |
| NCT | PT |


| RP | Revealed Preference |
| :--- | :--- |
| RUM | Random Utility Model |
| SDC | Socio-demographic |
| SP | Transportation Demand Management |
| TDM | Travel Time Difference |
| TTD | Value of Travel Time Savings |
| VTTS | World Health Organisation |
| WHO | Willingness to Accept |
| WTA |  |
| WTP |  |

## 1. Introduction

### 1.1 Disruptions in Metro Systems Operations: An Overview

In 2010, more than half of all people lived in an urban area, and by 2050, this proportion will increase to 7 out of 10 people ${ }^{1}$. Currently, around half of all urban dwellers live in cities with population between $100.000-500.000$, and fewer than $10 \%$ of urban dwellers live in megacities (defined by UN-HABITAT as a city with a population of more than 10 million) (WHO, 2013).

Along with population growth, metropolitan cities have experienced unprecedented growth in car usage in the last 20 years. To deal with this increase, Transit Authorities around the world are planning Metro (Subway) extensions to provide a framework for the overall future expansion. As we live in an era of globalised recession, the need for expanding Metro systems is vital and the need for these systems to serve the larger communities is ever increasing. The subway (Metro) system is considered as one of the critical lifelines of large metropolitan cities. Along with the road transport system, its ability to connect spatially different locations is vital for the accessibility and welfare of people and the economic efficiency of businesses (Jenelius and Mattsson, 2012). These systems are considered to be the most reliable public transportation modes as a result of their dedicated corridor and advanced technologies of operation. These systems also provide high-capacity performance and high frequency of service which is totally independent from other traffic, road or pedestrians. Due to their high capacity, Metros play a key role in reducing congestion in rapidly growing cities.

By 2010 worldwide there were over 160 systems in 49 countries and over 35 under construction (Urbanrail, 2012). It is not uncommon though for such systems to suffer from occasional disruptions. As Metro systems are usually integrated with and feeding into other modes of public transport, a sudden or unexpected or even programmed disruption of the system can significantly affect the entire network. Unlike buses, a disruption in a Metro line segment, a train malfunction or even a temporary loss of power will practically halt, prohibit, or restrain movement of trains along the line(s), since in most cases Metro lines cannot be detoured and locations of crossovers for turn-backs are limited and therefore, will adversely affect a large part of the Metro systems (Kepaptsoglou, 2009). Commuters disrupted by significant improvements of the subway network (e.g. new signal system, replacement track works) experience disturbances that

[^0]force them to alter routes or modes, to avoid disruptions. Transit strikes may reroute traffic, resulting in missed medical appointments, lost jobs, or curtailing of social activities (Urban Transportation Showcase Program 2012). These situations are of particular interest to transport operators as they need to plan ahead for such contingencies to avoid patronage loss in the long-term. Recent examples of subway closures in the London Underground (London Assembly Transport Committee 2011; 2012), the Metro de Madrid (Annual Report Metro de Madrid 2010), and the Athens Metro are cases where closures lasted from several days to few months. Following a major disruption, it is generally difficult to determine how long it takes for network operations to fully recover; travelers may either adjust their travel decisions or experience significant delays.

Subway network closures caused by events such as unforeseen technical breakdowns, strikes, or planned infrastructure upgrades are not frequent, but when they occur they disrupt public transport operations significantly. Kepaptsoglou and Karlaftis (2010) discussed how critical the protection against these failures is, and explained that any service disruption can result in the degradation of a subway's capacity, leading to unsatisfied demand and trip delays since commuters expect to arrive at the published time.

The protection of critical infrastructure against failures has been widely recognized by all European Member States in national and international activities (the legislative instrument for the European Program for Critical Infrastructure Protection is the Council Directive 2008/114/EC). These failures though, may be a result of both technical (maintenance and reliability) and anthropogenic causes such as personnel strikes and power outages.

When transit networks are disrupted - by transit strikes, major renovation track works and power outages - the routine travel behavior of millions of travelers can be affected particularly within congested metropolitan areas. Transportation disruptions may prompt drivers to begin using other types of transportation such as carpooling or even start telework, habits that may continue once the disruption is over. In that context, Transportation Demand Management (TDM) can help minimize such interruptions and is also a unique opportunity to implement new transportation initiatives (Urban Showcase Program, 2012).

Disruptions are unique opportunities for municipalities, employers and transport operators to implement new TDM measures such as guaranteed ride home programs, discounted transit passes, telework or flexible work hours and marketing an online information system for alternative transportation.

### 1.2 Demand Changes from Metro Line Closures

As discussed, establishing alternative means of transportation for Metro passengers in wake of a service disruption, is a key responsibility of urban transit authorities (Boyd et al, 1998).

During a Metro closure passengers may consider the following alternatives:

- Cancel the trip,
- Postpone the trip,
- Reschedule the departure time of the trip,
- Use alternative modes, walk, ride a bike, use existing or replacement bus services,
- Use carsharing or carpooling,
- Move to a friend's/relative's house to be closer to workplace, and
- Telework/Work from home.

The response of travelers to a Metro closure depends on the nature of the disruption that drives the above mechanisms. Disruptions vary from those which last a few hours to a few days or even a few months. It is also important to know whether the disruption refers to a full closure of the network or to a partial closure of the Metro network. The choice of mode also depends on the available information the passenger has on alternative transportation. The diversion of passengers to alternative modes depends also on socioeconomic criteria, car availability, flexibility of working hours etc.

Demand changes and potential changes in mode choice from Metro line closures play themselves out over long time horizons following a Metro closure and it is generally unknown whether they will have a permanent character. For example, a long-term closure of a Metro network may lead travelers to explore alternative routes which may be more attractive, force some to relocate or shift to car use.

### 1.3 Research Scope and Objectives

Despite their practical importance and the frequency of these disruptions, there are no available studies that examine the effects of a long-term disruption on traveler choice of mode during the closure. Planned closures may force passengers to adopt their temporary habit of altering route. In order to discourage commuters from shifting to their car and mitigate the impact of the closure on the road network, it is important to understand the reasons behind this choice and explore alternative ways to persuade commuters to stay on the public transport network post-disruption era. In this context, this research focuses on altered travel patterns related to Metro service disruptions. These include analysis of travel patterns during a Metro closure and the comparison with normal travel patterns. The study aims to explore altered travel patterns during Metro closures by exploring the reaction of three categories of travelers:

1. Travelers who remain on the partly disrupted network during the disruption and use the operating parts of the line and any alternative means -if any- provided by the operator for the non-operating parts of the line,
2. Travelers who during closure shift to alternative modes, and return to the Metro system after the line's restoration, and
3. Travelers who adopt an alternative mode even after the line's restoration.

For this analysis we use Revealed Preference (RP) and Stated Preference (SP) techniques to explore the importance of trip and traveler characteristics (i.e. travel time, cost, and previous experience of travel) on travel patterns during a Metro closure. The analysis uses econometric models and appropriate elasticities based on discrete choice theory to capture user preferences during a Metro closure. Key research questions are:

1. How does a Metro closure affect travelers? What are their reactions to such disruptions with regard to the choice of mode?
2. Which alternative mode do they use during the disruption?
3. How sensitive are Metro users to increased travel times during disruptions of Metro operations?
4. Which parameters play a significant role in choice of mode during a Metro closure?

We note that longer-term changes in passenger behavior (such as the relocation of homes or offices) were outside the scope of this work.

### 1.4 Research Approach

Figure 1-1 highlights major steps completing the research activities of the dissertation. The light blue boxes refer to the topics of the chapters.


Figure 1-1 Outline of the dissertation

## Detailed description of chapters

To give an overview of the structure of the dissertation, we will now look briefly at the contents of the chapters:

Chapter One: This chapter presents the purpose and outline of this dissertation. This includes an outline of key research questions of this dissertation, followed by an outline of the dissertation content.

Chapter Two: This chapter provides a state-of-the-art review which includes a review of studies on urban network disruptions (Metro and road) and travel behavior, along with a review on SP and RP preference travel surveys. This chapter also presents a review of existing work in the area of public transportation and emergency response and the use of questionnaires to assess user perceptions. The concept of Metro network disruptions is introduced and relations between various trip and traveler characteristics and mode choice are described. Chapter 2 also looks at the Stated Preference and Revealed Preference survey methods to capture user's preferences on mode choice. This is followed by a description of the orthogonal design method and the efficient design and a discussion on the reasons why orthogonal design was chosen. After a review of existing work on this area, the chapter discusses the development and design of the orthogonal survey, the fractional factorial design, and the design coding. This last section in chapter 2 aims to provide the reader with the essential concepts that have to be understood in order to avoid systematic bias and error related to SP design.

Chapter Three: A review on analytical tools and mathematical models used to analyze questionnaires that were collected for this research is presented in this chapter. This chapter presents the framework within which revealed and stated choices are modeled. It describes the methodological approach to a mode choice related problem. To assess the importance of the selected parameters related to trip and traveler characteristics after presenting the random utility theory and the theory of utility maximization we devote time in presenting one of the most basic discrete-choice models, the Logit model. We also discuss behavioral and econometric properties of the Multinomial Logit model (MNL), as well as direct and cross elasticities, probability predictions and marginal rates of substitution. We then present the key model structure of Multinomial Probit model (MNP), trying to relax the strong assumptions of MNL. The chapter looks at the use of alternatives to Independence from Irrelevant Alternative (IIA) models and specifically at
the Heteroskedastic Extreme Value models (HEV). This is followed by a brief in introduction of the Nested Logit model which, like the multinomial probit model, allows relaxion of the IIA assumption by splitting the alternatives into groups (nests).

Chapter Four: The case study area is presented in this Chapter. We provide a detailed description of the Athens Urban Transport System. The discussion of existing travel options within the Athens Urban Network will provide information about length of network of the Athens Metro System and daily patronage.

Chapter Five: This chapter presents the design of a RP questionnaire to study the impact of a 5-month Metro line closure. Chapter 5 acts as the introduction to the applied part of the dissertation. In this chapter we examine the impact of a real Metro line closure on the choice of alternative modes during the closure period. This is followed by an analysis of the impacts of the closure on commuters during and after the line restoration. The analysis uses Binary Logit models to explain the relation between various attributes and choice of mode during the 5 -month Metro Line closure.

Chapter Six: This chapter provides a detailed description of the design of a SP survey to capture users' preferences on choice of mode during a hypothetical Metro closure with regard to trip and traveler characteristics. Chapter 6 discusses the findings of an internetbased SP survey conducted to capture users' preference during a 24 hr scheduled Metro strike making use of a MNL, MNP and HEV Model. The survey also collects data on travelers' responses with regard to their choice of mode during a recent Metro disruption (if experienced). The responses to the survey and the results obtained from the questionnaires and the SP experiment are provided in this chapter. A discussion of the methodology and the results obtained is described at the end of this chapter.

Chapter Seven: This chapter discusses the advantages of combining multiple data sources to estimate the unknown parameters in the utility functions of both RP and SP models. The theoretical framework for the incorporation of different types of surveys in econometric choice models is also presented in this chapter. The analysis uses Nested Logit model to synthesize the datasets of RP and SP surveys. This is followed by a discussion of the methodology used, the use of a scale parameter to equalize the scale of the coefficients of the two models and the results obtained.

Chapter Eight: This chapter provides a summary of the work discussed in this dissertation, presents the conclusions derived from the entire research project, followed by specific research contributions and future recommendations.

## 2. Literature Review

The review presented in this chapter looks at existing work on public transportation and emergency response and the effects of such disruptions on travel patterns. We then discuss the two methods used to collect the appropriate data and then we discuss briefly the design and analysis of RP and SP techniques to assess user perceptions.

The discussion in this chapter is structured as follows: after a brief review of the different types of Metro disruptions in section 2.1, we look at various studies that have addressed the effects of public transport disruptions on travel patterns in Section 2.2. This is followed in Section 2.3 by a discussion of the impact of urban highway network closures, transit strikes, engineering works, human-caused disasters and terrorist attacks on traveler responses. We then look at various factors that affect the travel patterns of the affected population. In section 2.4 Transportation Demand Management measures are briefly presented.

In Section 2.5 we review studies that relate choice of mode and scheduling choice, while on Section 2.6 and 2.7 we review studies related to psychological factors affecting choice of mode, and factors affecting loyalty of currents users of transit, respectively. In section 2.8 we briefly present various methods of travel surveys while in Section 2.9 we present the SP method and its best-known techniques such as Orthogonal and Efficient design. We present a brief review of the main concepts of the methods and a detailed discussion of existing work on these methods. In Section 2.10 we present the RP technique and provide a brief review of existing work on this method. The chapter closes with a comparison of the two methods in 2.11, a description of the process of pooling RP and SP data in 2.12, and a summary in 2.13.

### 2.1 Types of Disruptions

Unlike disruptions in general, a transportation disruption can occur as a result of a subset of the drivers identified by Chopra and Sodhi (2004), which include natural disasters, labor disputes, terrorist activities and infrastructure failures/upgrade. A transportation disruption can fall in the category of supply-chain problem, as any disruption in the transportation network can seriously disrupt or delay people, material, and cause capacity issues in the entire transportation network. The response and the effectiveness of the measures taken by the transport operators, municipalities and authorities depend on the organization's level of preparedness and the type of disruption.

Valdés-Diaz et al. (2005) reviewed the ineffective system operations of transit systems. The authors report that disruptions are caused by several factors such as brake system failure, door failure, train control failure and incidents inside the vehicle. Among the first four causes of disruption on the Metro line of a total of 1156 incidents that the authors reviewed during the operation throughout a year are: disruptions associated with the brake system, automatic train control and station overrun (Valdez-Diaz et al., 2005). They also report that the disruptions that caused the longest delays are jump incidents (when an unauthorized person jumps on the tracks), fire and smoke, signal failure, track failure and propulsion and power failure. Other reasons may concern public related issues, or other miscellaneous events. Results indicated that the delay/headway ratio analysis could be a good indicator for heavy rail (Metro) systems. The authors also highlight the importance of an updated and accurate database of the distuptions occurring in the system.

Service disruptions may be either planned or unplanned. Planned service disruptions can be broadly categorized in the two following broad categories:

- Planned engineering track works
- Planned metro station closures for security reasons (e.g. major riots/protests in the city centre)

Pender et al. (2012) categorizes the causes of unplanned metro/train service disruptions:

- Intrusions/Medical Emergencies-includes suicides, track intrusions, railway crossing/incidents and sick passengers;
- Weather/Natural Disasters-includes extremes of weather (typhoon Sandy) such as snow and heat waves and natural disasters such as earthquakes and cyclones;
- Track-includes all track-related issues including problems resulting to power failures, signaling and crossovers;
- Other trains-includes disruptions caused by other passenger trains or freight trains that share the network; and
- Rolling stock-includes all rolling stock issues ranging from door obstructions to train failures
- Personnel Strike

Depending on the nature of the cause of the disruption, various types of responses to a Metro closure may be observed.

These may include:

- Some trips will be cancelled.
- Some trips will be delayed.
- Some trips will be postponed to later start or finish time.
- Travelers will shift to alternative modes.
- Travelers will adopt the alternative modes if satisfied.
- There will be a loss in patronage and dissatisfied travelers.
- Longer travel times: this may occur either because travelers are forced to take circuitous routes from origin to destination to avoid impassable links, or as a result of traffic congestion that is caused by the diversion of traffic away from impassable links.
- Increased travel cost: this may occur either because travelers are forced to travel by car to destinations where parking is not provided free for them, or pay an extra fare to travel by taxi, or even share the cost of traveling by car with someone else.
- Increased travel inconvenience and general dissatisfaction due to longer travel times, increased travel cost and uncertainty in arrival times. As a result of the traffic congestion, Public Transport Modes are expected to offer unreliable services (more crowding, longer travel times unless running on dedicated bus routes).

The size of the disruptions is affected by various factors. These include (TRB Special Report, 2008):

- Advance notice/no notice: an important factor because it allows time for travelers to make decisions in advance of their route and consider all alternative routes and modes. In case of no notice, Metro users are required to act immediately.
- Type (natural/human caused)
- Time period of day/week (peak, off-peak, weekday/weekend)
- Duration (hours, day, months): the time of the day is a significant factor as safety issues may arise during night and travelers may consider safer ways of travel. It is also important if considered in relation to the purpose of the trip. Most trips during weekdays are done for commuting purposes and cannot be cancelled or postponed on a frequent basis, while trips during weekends are related to social activities and may be easily cancelled or postponed.

Regarding the transit system the factors that affect the size of the disruption can be summarized below:

- Size of the network
- Characteristics of the urban area/population
- Population of the urban area affected (size, density)
- Socioeconomic characteristics
- Population age
- Income
- Immigrants-cultural: cultural ethics are also important as some people are heavy users of transit
- Communication and information systems are also important as these systems may prove very useful and helpful in a programmed or even unexpected event. The need for transit operators to provide information of the incident and inform the public of replacement services if they exist or alternative routes is vital. This notice has to be translated in multiple languages.
- Travelers' previous experience with a closure: this factor is considered very significant as travelers' (public) previous experience with closures of the Metro system and good knowledge of the transportation system can affect their travel route chosen during the incident.


### 2.2 A Review of Metro Service Disruption Studies

Although major incidents such as network disruptions, train accidents, fires, floods, and terrorist attacks occur from time to time and have been an issue for transit agencies and transit management since the development of modern public transportation (Boyd et al., 1998), previous research on the effects of transit service disruption is limited (Balog et al., 2003; Zhu et al, 2008). Existing studies showed the important role of experience in travel decisions, which has been frequently expressed in theoretical studies (Zhu S. et al, 2008). Early work has focused on emergency management and general analysis of travel behavior during Metro closures.

As reported earlier in Section 2.1 many trips that occur despite a Metro closure will take much longer. As a result there will be lost days or even days. Lost sales, lost production, and longer commuting travel times, due to circuitous travel or traffic congestion. Crisis situations (i.e. transit system disruptions, fuel shortages) are unique opportunities to implement actions that under normal circumstances would not be adopted or would require a long project approval process (Meyer and Belobaba, 1982). Table 2-1 summarizes briefly the findings of related studies to transit strikes as reported by Zhu and Levinson (2011).

Table 2-1 Related studies to transit strikes (Source: Zhu and Levinson, 2011)


Though strikes in public transport occur frequently, studies of strikes are rare (Van Exel and Rietveld, 2009). Van Exel and Rietvield (2001) reviewed 13 studies of strikes in
public transportation systems between 1966 and 2000 - in Europe and in the United States - to determine their effects on travel patterns. Results indicated that captive users are the ones affected the most, particularly commuters without alternative modes of travel. They concluded that between $10 \%$ and $20 \%$ of travelers - mainly commuters cancelled their trips altogether. This percentage was much higher for trips by the elderly and the disabled, as well as for leisure trips. Most travelers switched to private cars while others used bicycles, alternative modes of public transport, or shared rides with friends and colleagues. As this study refers to a previous century and may be considered out-ofdate in year 2013, the need to update the findings of this study and enrich with new data from actual Metro closures in the city of Athens is more critical than ever.

In recent years, London's Metro (tube) has experienced some of its most severe winter weather resulting in extensive disruption to transport networks and travel problems to millions (DfT, 2011). Except for closures due to extreme weather conditions, London's Tube weekend maintenance closures raised concerns to transport authorities as for losses in ridership. As reported from the Transport Committee of London Assembly, traveler "key irritations" during Metro upgrade works are longer journey times, "broken journeys" and paying for a substandard service. The Committee's report shows that passengers are forced to adjust their lives to accommodate Metro closures, often by cancelling journeys or, in the case of evening closures, by changing social arrangements in order to travel home earlier. Passengers are particularly sensitive to multiple line closures affecting a particular area and closures which coincide with big events such as sporting events (London Assembly Transport Committee, 2009).

Bjornskau (1999) describes the effects of a 26 -day bus strike in Norwegian cities. He argued that during the strike some travelers chose to work at home or take time-off, but the majority went to work. However, many people travelled at other times. As expected, traffic increased substantially in the cities, but the road traffic increase in the Oslo area was quite modest, possibly because of the extensive Tram and Metro networks available.

For nearly a month in the region of Ile-de-France (Paris and surroundings), almost all public transport was affected by a strike (Coindet, 1998; Lapiere, 1998). About $50 \%$ of captive public transport users switched to car, thus resulting in increased congestion and journey times to work by $70 \%$. Commuting behavior was almost fully returned once the strike was over (Coindet, 1998).

Planned closures may provide commuters with the opportunity to explore alternative ways to commute and especially adopt this temporary habit to routine (Zhu and Levinson, 2010; Van Exel and Rietvield, 2001). To minimize the percentage of commuters who shifted to car and mitigate the impact of the closure on the road network, it is important to understand the reasons behind this choice and explore alternative ways to persuade commuters to stay on the public transport network postdisruption era.

Darmamin et al. (2010) examined the consequences of distuptions on the Metro Train Melbourne and developed a mathematical model to minimize commuter discomfort; the model included a number of operational constraints. They proposed using existing bus lines as an alternative to deploying charter buses during a disruption.

Harris and Ramsey (1994) examined passengers' short-term responses to service disruptions on London Underground Line using appropriate elasticities. The authors applied a network modeling software to simulate passenger response to system failures caused by the life-expiry of the physical infrastructure, in order to estimate the passenger disbenefit and the interchange penalties. Their modeling assumes that the generalized cost of a trip is an expression of different elements of a journey (fare, waiting time, access/egress time, in-vehicle time, and error term). Their analysis indicated that the effects of the closure were not only felt by passengers attempting to travel on the affected line segment. Due to limited capacity of some train reversing points, trains were running on reduced frequencies leading to a less attractive service through longer waiting times and increased crowding. The model suggested that many passengers would forego the trip rather than make it by public transport with the likely disbenefit of at least 20 minutes per single journey.

Pender et al. (2012) explore the manner in which rail transit organizations plan for and manage unplanned service disruptions through interviewing staff responsible for service disruption management of 48 transit agencies. Bus bridging was reported as the most common response to line blockages. Results from the same study suggest that only $11 \%$ of agencies had parallel transit systems which can be used for riders on disrupted services. The authors report that most agencies used available spare buses to source bus bridging vehicles, however it didn't cover the entire rail corridor ( $63 \%$ ), or even if it did run along the disrupted corridor, there would be capacity restraints ( $6 \%$ ).

Planned or unplanned degradations of the subway transport system may have severe consequences and affect the entire transport system (primarily the road network and the bus network), of a large metropolitan area. Although this problem is quite significant, researchers have mostly explored disruptions in the road transport system (Wesemann et al., 1996; Zhu et al., 2010). In summary, travel-pattern changes during disruptions in transportation systems have not attracted considerable interest in the literature, despite the practical importance it has for planners and policy makers. Disruptions on Metro systems resulting from maintenance upgrade works occur occasionally; however, there are no available studies that examine the effects of a long-term distuption on traveler choice of mode during the closure.

Though highway networks and public transportation networks are different, the same principles apply behind the demand-supply chain. Still, the differences between highway network closures due to natural disasters and transportation system disruptions are substantial. In the latter case, more advanced warning is given in most cases. However, we may assume that the mechanisms behind the choice of mode are more or less the same and the insights gained on travel patterns gained from road network closures are relevant to urban public transportation disruptions.

### 2.3 A Review of Studies related to Urban Highway Network Closures

Although a comprehensive review on the literature on urban highway network closures is given in this section, particular emphasis is placed on transportation systems disruptions and their effects on travel patterns.

Highway network closures due to human-caused disasters or major accidents have attracted attention in the past. Several studies have examined the travel behavior impacts of major reconstruction projects (Fujii et al., 2001; Devine et al., 1992). Various studies have quantified the effects of a strike on traffic (Sermpis, et al., 2007), mainly exploring the change in the modal split of the trips (Marmo, 1990; Blumstein and Miller, 1983; PbIVVS, 1984; Bonsall and Dunkerley, 1997), and the extension of peak-hour periods (Coindet, 1998; Lapierre, 1998; Lo and Hall, 2006).

Sermpis et al. (2007) describes the effects of a 24 hour strike of all Public Transport modes, on the road network on December $15^{\text {th }}, 2005$ in Greece. The authors argue that the strike would not result in the mode shift of all trips made by public transport modes to alternative transport modes due to the participation of Athenians to strike, who would
cancel their trips to work anyway. The authors estimate the effect of the strike on the traffic patterns in the Athenian roads by analyzing traffic data on major arterials. The traffic data of that day was compared to the average values of all Thursdays of a typical 3 months period.

Post-disruption travel pattern changes in transportation systems has attracted only limited interest in the literature, despite the practical importance it may have for planners and policy makers. Gigerenzer (2006) investigated reactions of US airline travelers following the attack on September 11th. He suggested that for almost a year following the attack, Americans reduced air travel and a proportion of those who did not fly, drove to their destination. He also argued that the attack caused significant 'indirect impact' on people choices, keeping them away from their usual choice of transport mode for longer periods of time compared to the effect of the bombing attacks in Madrid in 2004.

Fasolo et al. (2008) examined traveler responses to the terrorist attack on July $7^{\text {th }} 2005$ in London. Their dataset included weekly passenger volumes in the London Underground and Buses from 2002 to 2006. Findings showed a $12.8 \%$ drop in weekday subway ridership in the week following the attack. They also found that Londoners avoided the two modes attacked by terrorists and instead started using bicycles and motorcycles.

### 2.4 Transportation Demand Management and Contingency Planning for Network Disruptions

When transit networks are disrupted - by transit strikes, major renovation track works, extreme weather conditions, power outages - entire cities can be affected. Transportation demand management (TDM) can help minimize such interruptions and is also a unique opportunity to implement new transportation initiatives (Urban Showcase Program 2012). Transportation disruptions may prompt drivers to begin using other types of transportation such as carpooling or telework, habits that may continue once the disruption is over.

Disruptions may become unique opportunities for municipalities and employers to implement new TDM measures such as guaranteed ride home programs, discounted transit passes, telework or flexible work hours and creating an online information network for alternative transportation. In the city of Ottawa for example, in December 2008, transit personnel went on a 50day strike. To mitigate the effects of the strike, a series of initiatives were designed to help commuter travel. The measures included maintaining primary walking and cycling routes, providing discounted car parking rates
for car-poolers, offering a bus-lane to improve traffic flow, and assisting elderly and those with disabilities with paratransit service. The measured impact of these measures (a month after the strike ended) indicated an $18 \%$ increase in transit ticket sales and $6 \%$ in transit passes.

The area of Urban Transportation System Disruptions is not new. It has been subject of research for many years, especially on the side of contingency planning. Meyer and Belobaba (1982) examined contingency planning processes used in three different emergency situations with serious gasoline shortages and with interruptions to urban mass transit services. The authors reviewed the implementation of the contingency measures taken from three different authorities in three US cities during these disruptions in urban transportation services. Note that, at that period (in the 1980's) with the increasing uncertainty over government subsidies for public transport, the likelihood of future disruptions to urban transportation systems was quite high, as it is today in 2012.

Key approaches under either scenario are (Pender et al., 2012):

- Commuters to make use of alternative transport
- Altering train stop patterns
- Bus bridging
- Hiring taxis
- Improving frequencies of existing bus routes
- Suspending service and offering no alternatives to disrupted commuters
- Re-routing trains onto other operating train lines of the same network


### 2.5 A Review of Mode and Scheduling Choice

The possibility of flexible working and scheduling choice possibly has some effect on choice mode. But what about during Metro closures? Is this factor considered also significant during such events?

McCafferty and Hall (1982) estimated a Multinomial Logit model of three period departure time choices and then tested its stability by re-estimating the model after an exogenous effect of road closure which is expected to affect the schedule choice. Though
they estimated their model with only people with flexible working hours, their results showed a strong bias towards travel during peak hour. The conclusion the author reached was that this is evidence that flexible working hour may not be an important factor in schedule choice and probably it is guided by some other socio-economic factors.

Hendrickson and Plank (1984) also argue that mode choice should consider scheduling choice as characteristic of travel varies by time of day. The authors used data collected in Pittsburgh, consisting of 1800 workers in Central Business District and independent measurement of travel times and transit wait times. They estimated a logit model of simultaneous mode and schedule choice. Their value of time calculations show that access time to transit was the highest value followed by the waiting time. They also showed that lateness is more onerous than early arrival.

Pells (1987) argues that people decide on a safety cushion (time allocated for unexpected delays). It is generally assumed that early arrival is more onerous than staying home and they also value late arrival more than staying at home. Thus people maximize the time spent at home subject to the constraint of tolerable lateness. The author estimates the slack time substitution effect by a SP experiment. People were asked to select between pairs of travel time in which one had a reliable arrival time and the other was a cheaper option with some degree of risk. People seem to leave home later as the reliability of service increases.

### 2.6 A Review of Psychological Factors and Mode Choice

Mode choice is believed to relate to several psychological factors including habits, social norms and attitude (Heinen, Van Wee \& Maat, 2010). Johansson and Helt and Johansson (2006) support the selection of psychological factors in mode choice selection as they found these attributes to be more explanatory than gender and age. Other factors to influence mode choice as reported in the literature are the preference for convenience, comfort and flexibility (Johansson and Helt and Johansson, 2006).

Although discrete choice modeling assumes that people always consider every factor or alternative for their trip decisions, this is not true in repetitive decisions. Gerike, Bamberg and Shmidt (1994) support that travelers rely on the decision making process that they employed last time they were required to make the choice.

Previous research on past behavior or on habit measure has not reached a conclusion on whether a general habit can have an effect on mode choice. Bamberg et al. (2003) support that former car users show a strong behavioral reaction even to small, relatively inexpensive interventions. The data used did not support the hypothesis that habit influences behavior.

### 2.7 A Review on Factors Affecting the Loyalty of Current Users of Transit

Li et al. (2013) proposed a method of analyzing factors which affect the loyalty of current users of transit. Their analysis concluded that transit service quality is the most important factor impacting transit passengers' willingness to pay. The authors define service quality as a stream of 7 variables (comfort, timeliness, reliability, convenience, freedom, economic cost and freedom). Four of these variables (comfort, safety, convenience and timeliness) were found to play a decisive role. The authors fail to find evidence on supporting that the improvement of transit service quality could lead to a mode shift of car users to transit or restrain transit users from using car. In this study though, transit users were restricted to commuters who do not own a private car.

### 2.8 Travel Surveys

Surveys can be distributed in person, on the phone, through the mail, via a web site, or email, etc. Internet-based surveys have started gaining ground recently and are mostly preferred as they are less-expensive and time consuming. Before launching a survey it is advisable to have a focus group testing the survey and giving feedback. This group of people will discuss the individual questions, correct and update if necessary. Just after evaluating the survey from a group of professionals you need to test it on random people.

In the past social media were used for marketing, political candidates for their election campaigns, information networks for news updates, companies for recruitment and, most recently, nations for revolutions (Efthymiou and Antoniou, 2012). The authors conclude that this type of data collection is preferable for transport surveys, since they are integrated with email providers. This method has been used in other related transport surveys (Amey et al., 2011; Bregman, S, 2011; Grigolon et al., 2011). Another survey conducted by Focus Bari, in $2010^{1}$, reported that only $29 \%$ of people aged $35-44$ use

[^1]social media. The same shares increase for younger people aged 34 and less ( $52 \%$ of people aged $25-34$ and $72 \%$ of people aged 18-24).

Web surveys can track responses using IP addresses and may reduce bias, as it is able to track responses from people living outside the target area. It may also reduce bias since it records the total time needed for completing the survey. It is assumed that long recorded times may reveal fatigue during questionnaire completion and it would be safer to be excluded from the final data sample. The reasons why researchers prefer to collect data based on web surveys are (1) the web-based survey is relatively inexpensive, (2) may be easier for respondents to answer, (3) is environmentally friendly, (4) it has quick response time and saves considerable processing effort and (5) question branching is straightforward, so only the relevant responses are presented based on responses to earlier questions (Bhat and Sardesai 2006). As Dilman (2000) notes, the use of electronic media poses new and different issues regarding strategy, design and dissemination of a survey. For regular internet users, the Web has been found to be a useful means of conducting research (Kaaplowitz et al 2004; Couper 2000). However, with internet-base surveys the researcher cannot control the target group and surveys do not reflect the general population.

As expected internet-based surveys are vulnerable to biases. Theoretically the collected sample should be random, and it should cover all ranges of age, income and educational level (Efthymiou and Antoniou, 2012). However, according to a recent research in Greece only $35 \%$ of people aged 45-54 used the internet in the last trimester of 2010 (www.observatory.gr). The shares drop for people aged $55-64$ to $15 \%$, while the highest share of people that use internet falls in the category of people aged 16-24 years old. Only $49 \%$ of men used the internet the internet in the last trimester of 2010, while the same share drops to $40 \%$ for women. Not surprisingly $76 \%$ of highly-educated people used the internet in the last trimester in 2010 in Greece, while only $16 \%$ of low educated people did use it.

Among the candidate survey softwares we chose kwiksurveys software (www.kwiksurveys.com). Other commercial softwares are Surveymonkey (www.surveymonkey.com), Google Documents (google docs), wuffo (www.wuffo.com), and surveygismo (http://www.surveygizmo.com).

### 2.9 A Review on Stated Preference Techniques

The decision making process of people under emergency/disruption conditions is a very complex issue influenced by a number of different factors, such as the type of the disruption, informer, socio-economic characteristics of users, and previous travel experience. On the other hand, the prediction and accurate simulation of user behavior is essential to optimize the emergency response and management system and minimize the effects of the disruption on the entire network and population. To deal with these problems and determine the independent factors that influence the decisions made by individuals, we use available data or in the absence of any data we organize the collection of relevant data.

Historically, there have been two methods for collecting data: RP and stated choice methods. In the first method, we usually ask respondents to reveal their actual choices. In cases of Metro line closures, ridership is affected as a result of passenger shifting to alternative modes (buses, private cars, taxis). However, this behavioral change is not identical for all travelers. It frequently has only short-term effects, with many travelers reporting that they do change back to using the Metro once the service is restored (Rubin et al., 2005). These situations are of particular interest and hence need to be analyzed in two phases: i) during the closure of the subway network and ii) long after the system is restored. To explore the change in travel patterns during the closure we would use RP data, because these techniques explain better actual behavior. To be more specific, RP data collected by observing data in real situations are used in this research study to interview two categories of travelers:

- Travelers who post disruption return to the usual mode of transport and therefore, can be easily identified and interviewed,
- Travelers who during the disruption used alternative modes for the disrupted part of the line, and following the disruption continued using the Metro lines.

However, in order to capture those travelers who intentionally shifted to alternative modes during the closure we need to use SP data, because we are dealing with a hypothetical scenario of a subway closure that travelers may or may not have experienced in the past. As mentioned in Chapter 1, the scope of this dissertation is to analyze the travel patterns of the affected travelers.

SP methods belong to a family of statistical tools which use disaggregate data to capture personal preference of public regarding a hypothetical set of choices (in our case in the transport area), in order to develop utility functions of each mode.

The purpose of this section is twofold:

- to describe briefly the benefits of developing a statistical tool so as to investigate the responsiveness of potential and actual participants in a programmed 24 hr Metro closure, and
- to demonstrate the benefits of using an SP design.


### 2.9.1 Review on Stated Preference Studies

Since SP data represent choices 'made' or stated in hypothetical situations, it may lead to situations where the respondent does not consider personal constraints at the time of the choice. The realistic design of the SP experiment should make the hypothetical situations as realistic as possible. The mathematical and statistical data analysis of these methods leads to the development of mathematical models that give the researcher the opportunity to decompose the overall preferences or choices as provided by the respondents into utility weights associated with the factors (Kroes and Sheldon, 1988).

SP methods use specially constructed questionnaires to elicit estimates of the Willingness to Pay (WTP) for or Willingness to Accept (WTA) a particular outcome. WTP is the maximum amount of money an individual is willing to give up using a mode in our case. WTA is the maximum amount of money they would need to be compensated for foregoing a good (switching to another mode) (HM Treasury, 2011).

The beginning of SP methods/techniques goes back to the early 70 's when these methods were initially developed and used in marketing and are very widely used ever since. In transport, these techniques first received attention in the United Kingdom in 1979 (Kroes and Sheldon, 1988). First publications were by Steer and Willumsen (1981) and Sheldon and Steer (1982). A SP observation is where one can measure what individuals say they would (hypothetically speaking) do in a given context. The context may be a planned policy such as the introduction of a light rail system, or the introduction of a hypothetical closure of the current transport network.

The methodology adopted to capture all users preferences and responses to Metro closures included the design and implementation of a RP survey and a SP survey. In the
former case RP data were collected on travelers that either remained on the distupted network during the Metro closure or returned after the line's restoration. In the latter case RP data were not available and SP data were essential to capture the preferences on choice of mode of all users plus the travelers that never returned to the disrupted network, but even after the line's restoration adopted an alternative mode.

SP data have been used to study many transportation related problems over the past two to three decades, since they can be powerful instruments for studying hypothetical scenarios (Bliemer et al., 2009). Examples of this approach in the transportation planning field include Hensher (1994) and Abdel-Aty et al. (1995). SP methods have been proven useful when attempting to respond to a variety of transport research questions including estimating demand elasticity for various service attributes including fare, frequency and journey time (Kroes and Sheldon, 1988). SP techniques are more flexible than RP methods because the individual can be presented with trade-offs and with hypothetical questions/scenarios (Fawkes and Wardman, 1988). One of the most important advantages of SP methods is that it gives researchers the opportunity to collect more than one response per respondent and to extend the range of attribute levels.

However, since SP data are used to explore traveler patterns in stated and hypothetical scenarios, SP studies are commonly criticized since they suffer from a variety of biases. The primary drawback to SP data is that the patterns they depict is not observed (Mitcell and Carlson, 1989), and thus they fail to take into account certain types of real market constraints (Louviere et al., 2000). Further, individuals may not necessarily do what they say (Kroes and Sheldon, 1988). Recent research indicates that combining stated and RP questionnaires builds on the strengths and diminishes the drawbacks of each method (Hensher and Bradley, 1993). In this study we focus on the analysis of the SP experiment with respect to socio-economic characteristics of the travelers and questions regarding usual mode of travel, usual travel time to work and flexibility of working hours, because we target on all captive Metro travelers, even those who did not remain on the subway network during the closure.

### 2.9.2 Stated Preference Techniques

There are several techniques within the SP family including the contingent valuation method and the choice modeling method. Among those SP approaches are: (a) stated intention, where respondents are asked to hypothetically state their intentions of action, (b) ranking, which is considered difficult for middle-range alternatives and it is often
replaced by best-worst approaches, (c) rating, which may differ greatly across respondents and (d) transfer price or Willingness to Pay. The last one is subject to bias especially when respondents hope to achieve some kind of discount or cheaper ticket in a new introduced mode.

- Contingent valuation: when using this method the researcher needs to determine the value by asking a willingness-to-pay or willingness-to-accept question. This method focuses on the valuation of a non-market good as a whole; and
- Choice modeling: in this method you typically present respondents with a series of questions with a series of alternative descriptions of a transport mode or a transport management strategy. The experiment consists of a set of SP games and in each game the respondents are asked: "Which of these alternatives would you choose?" Each alternative consists of attributes and attribute levels, for example the alternative Rail has three attributes: travel time, travel cost and transfer. The levels of the values that are allocated to these attributes are called attribute levels. This method focuses on valuing specific attributes of a non-market good.

Hypothetical bias of choice experiments is becoming a major question in transportation research (Hensher, 2010). The author suggests and offers sensible directions for specifications of future choice studies:

1. the inclusion of a well-scripted presentation (including cheap-talk scripts), explaining the objectives of the choice experiment,
2. inclusion of the opt-out or null alternative, avoiding a forced choice setting unless an opt-out is not sensible,
3. pivoting the attribute levels of a choice experiment around a reference alternative that has been experienced and/or there is substantial awareness of, and estimating unique parameter estimates for the reference alternative, in order to calculate estimates of marginal willingness to pay for an alternative that is actually chosen in a real market,
4. the inclusion of supplementary questions designed to identify the attribute processing strategy adopted, as well as a question to establish "the confidence with which an individual would hypothetically purchase or use the good (or
alternative) that is actually chosen in the experiment"; the latter possibly being added into the choice experiment after each scenario and after an additional response in the form of a rating of the alternatives.
5. identifying constraints that may impact on actual choices that might be ignored in choice experiments, which encourage responses without commitment. Once identified these constraints should be used in revising choice responses.

The usefulness of these methods is because:

- We can estimate the demand for alternative transport services or new attributes to existing services,
- We can examine how individual choices differ by age, gender, income, trip purpose, etc.

We can examine hypothetical situations that do not exist in real life.
Recently, Train and Wilson (2009) introduced an SP-off-RP survey method, similar to contingent valuation method, where they ask the users if they would change their choice under specified conditions. Respondents are not asked to determine their willingness to pay directly as in contingent valuation.

### 2.9.3 The Null Alternative

Choice experiments and contingent ranking experiments usually include the status quo or "do nothing" alternative (HM treasury). This element is particularly important when conducting a SP survey and is called the "null alternative". In choice modeling techniques the "null alternative" refers to the "do nothing" scenario where the project is not implemented. The inclusion of the "null alternative" in the survey has two advantages: a) first guarantees that the estimations are in conformity with the economic theory, b) avoids bias by some people to unreasonably respond to some questions.

However, there are some researchers who might support the idea that the "null alternative" might give the opportunity to some respondents to choose the easy way to respond and avoid the tough questions. We will discuss in later chapters why we do not include this alternative in our experiment.

### 2.9.4 Drawbacks of Stated Preference Methods

Respondents of SP surveys may not always make the coherent choices they are expected to, because most times they are affected by survey context and various information cues as well as the order of choice tasks in choice experiments (e.g. Ajsen et al., 1996, Carlsson and Martinsson, 2008, Day et al., 2012, Ladenburg and Olsen 2008, Louviere 2006). This issue is known as ordering effects. Day et al. (2012) provide a discussion of different explanations of ordering effects. The first one is preference learning which explains how respondents gain familiarity with their own preferences and their decisions become less coherent and 'less random' (Carlsson et al., 2012). The second effect relates to the fact that most respondents participating in SP surveys have never participated in this type of survey before. The third effect is fatigue as respondents may experience fatigue when asked to respond the choice task many times. Kahneman et al. (1982) identifies the fourth effect which potentially causes ordering effects is the starting point ordering effect. He explains that respondents who are uncertain about their preferences regard a presented price as a cue to the "correct" value for that good. Fifth and sixth effects are both related to the fact that respondents may act strategically. Finally, it is highly possible to not include all relevant attributes in the survey design.

SP methods suffer from hypothetical bias (Harrison, 2006). Respondents in SP might not answer truthfully and answer in ways that they think will affect the outcome (Train and Wilson, 2009). In contingent valuation methods participants may declare amounts they are not willing to pay, while in choice modeling surveys they may underestimate the importance to the monetary attribute, and thus, favor alternatives they would discard in reality. Furthermore, respondents may experience inertia in actual choices while stating in the SP that they might switch mode.

### 2.9.5 Selection of the Alternatives, Attributes and Attribute Levels

To create an experimental design, the researcher must first define the alternatives, attributes and attribute levels that are to be used in the choice situations.

- Alternative: the options amongst which choices are made. The approach used for this analysis was to make a subjective selection of the significant alternatives.
- Attributes: the features that describe each alternative. These are the independent variables. The attributes included in the choice experiment may be common among the alternatives, such as departure time, or may be alternative specific, such as the access time or the number of transfers on a public transportation journey.

The number of attributes that may significantly affect the preference formation of the decision makers can be quite extensive. However, it is beneficial to limit the number of attributes that are included in a choice experiment for a number of reasons (Louviere, Hensher \& Swait, 2000). According to Hensher, Rose and Greene (2005) it is important to carefully choose the attributes of the alternatives to avoid inter-attribute correlations. In these cases usually decision-makers make assumptions on the level of one attribute based on the level of the other correlated attribute which may lead to bias.

- Values: the numerical values or categories assigned to an attribute.
- Levels: the numerical values of categories assigned to an attribute. Hensher, Rose and Greene (2005) report that the number of attribute levels included in the experimental design affects the ability of the analyst to distinguish non-linear relationships between the value of the attribute and the derived utility. Therefore, the analyst must find a balance between choosing enough attribute levels to discern the nature of the relationship between the attribute and the derived utility, and restraining the size of the experimental design (ChoiceMetrics 2011). In our experiment we used RP data to set the maximum and minimum attribute levels to reflect reality in order to create realistic choice situations for the travelers.
- Scenario: the situation which the respondent is asked to evaluate, made up of the alternatives.

Once the analyst has determined which alternatives to include, which attributes to consider and at what levels, the mean of the presentation (paper-survey, computer aided personal interview, internet-based survey) and the experimental design method must be considered. The core part of a SP technique is characterized by the statistical design to construct hypothetical alternatives and scenarios presented to the respondents.

The statistical design of attributes and attribute levels can be based either on full factorial, fractional factorial design or on efficient designs. These three are the most commonly used methods which are briefly summarized in the following sections. The aim of these designs is to maximize information on user preferences with limited number of observations. Researchers suggest if possible to base variations on the levels of attributes around values for observed trip. This information may arise from a pivot survey or as an alternative in the survey.

### 2.9.6 Full Factorial Design

This experimental design is the most comprehensive type of design since all combinations of possible situations are considered. An experimental design is called "full factorial" when every possible combination of attribute levels is presented to each respondent and is asked to select one of the alternatives. In a game of N alternatives, of M attributes of L Levels each, a full factorial design produces LMN games. We can also make this design using a fractional factorial design with $\mathrm{N} * \mathrm{M}$ columns of L levels. For example, a design with two three-level attributes and two two-level attributes would have $32^{*} 22^{*}=36$ scenarios. In a full factorial design dominant questions exist. These questions if presented to the respondents reduce reliability. Even in a fractional factorial we may have dominant questions. The only way to solve this problem is through efficient design of SP game. Hensher, Rose and Greene (2005) suggest avoiding this type of design since the workload for respondents is extremely large and causes fatigue to the respondents, while their effort to analyze the alternatives and select the most favorable one has been found to decrease.

### 2.9.7 Fractional Factorial/Orthogonal Design

Full factorial designs are practical only for small problems and even though they possess statistical advantages over full factorials these designs are rarely used. There are cases where the number of all possible combinations of attributes is too high and need to be reduced. This is the case where fractional factorial design solves the problem. In the fractional factorial design interaction terms are not orthogonal. Between main effects though orthogonality is preserved. Louviere, Hensheir and Swait (2000) support that since some interactions are not significant to the researcher fractional factorial design is widely supported by researchers. Fractional factorial designs are used because otherwise respondents have to face and respond to a large number of scenarios and experience fatigue, thus increasing the response error. Likewise, a large number of attributes or levels may lead to some items being ignored by the respondents (Permain et al., 1991). To reduce the size of full factorial designs researchers select a particular subset or sample of full factorial so that particular effects of interest can be estimated as efficiently as possible. Scientists have developed a series of tools of sampling methods that lead to practical fractional factorial designs.

Orthogonal designs are the most commonly used. A design is called orthogonal when all attributes presented to respondents are varied independently from one another. In orthogonal design there are zero correlations between attributes. In orthogonal design
the analyst typically uses orthogonal coding for the labeling of the attribute levels. This is achieved when the sum of a column of attribute levels equals zero. For this reason the attribute levels would be labeled $-1,0$ and 1 .

Since the number of all possible combinations may be significantly high, the researcher can reduce the number of combinations by using a subset of the full factorial design called the fractional factorial design, so that particular effects of interest can be estimated as efficiently as possible (Louviere, Hensher and Swait, 2000). In a fractional factorial design, we ignore some of the interactions except for main effects. In this design, the researcher should assume that some interactions are not statistically significant and ignore them. To avoid ignoring significant interactions we can control which interactions to be orthogonal. In our study we developed our orthogonal design in SPSS.

Louviere, Hensher and Swait (2000) concludes that even if interactions are significant and large, they rarely account for a great deal of explained variance. The authors suggest using designs that allow estimation of (at least) all two-way interactions whenever possible because main effects and two-way interactions account for virtually all the reliable explained variance. Rose and Bliemer (2004) though support that the orthogonality will be lost if one question is not responded/omitted by the respondent. For this reason respondents should be forced to fill out all questions.

According to Louviere, Hensher \& Swait (2000) the minimum number of choice situations that should be included is six, but depending on the number of alternatives, attributes and attribute levels included in the experimental design, the minimum number of choice situations can be significantly higher. To reduce the number of choice situations that are assigned to each survey respondent, a method known as blocking is used to orthogonally split the design into several smaller designs (Hensher, Rose \& Greene 2005). Each of the smaller designs is no longer orthogonal within itself, but the sum of the designs maintains orthogonality. The orthogonality of the design is preserved only if the complete design is used. The acknowledgement of this fact has been largely ignored by academics and practitioners, according to Hensher, Rose and Greene (2005).

An orthogonal design-data does not necessarily mean that the estimation data will also preserve orthogonality. The addition of socio-economic variables in the utility function leads to loss of orthogonality. This is very important for the most common procedure travel behavior modeling of estimating an MNL model (Hensher and Barnard, 1990).

The main reason to preserve orthogonality is to avoid multi-colinearity between variables (Sanko, 2001).

### 2.9.8 Efficient Design

For some designs, orthogonal solution (with limited number of rows) does not exist. For other designs, orthogonal solution may not be desirable because it may include dominated choices or rows where all alternatives are the same. Such choice situations may in fact cause serious problems. In this case, some practitioners choose to manually remove or correct the specific rows. This practice though is not recommended because it is likely to affect orthogonality. A possible solution would be to use a random design (where sample size requirements would be enormous) or produce an advanced design technique called efficient design (Figure 2-1).

Another reason for moving away from orthogonal design is the high cost of data collection and the difficulty of producing orthogonal design for large data samples. Recently, researchers started supporting the use of efficient designs. This type of design requires full knowledge of the beta coefficients of the parameters in the utility functions. In many case, we have preconceptions about the sign and the relative values of any marginal utility effects. This type of information is not used in orthogonal design. If this information exists, efficient designs outperform the orthogonal designs. These designs aim to increase the statistical efficiency of the experimental design (Hensher, Rose and Greene, 2005).


Figure 2-1 Flow chart for the modified Federov algorithm (Choice Metrics, 2011)

Efficient choice designs make use of prior utility functions and attempt to determine attribute level combinations that minimize the elements in the asymptotic variancecovariance (AVC) matrix. After creating an initial design, which can be either random or orthogonal, the practitioner needs to calculate the choice probabilities for each alternative in the design and construct the AVC matrix for the design. Various measures have been proposed in existing literature to estimate and evaluate the statistical efficiency of the design. The most commonly used is the D-Error:

$$
D-\text { error }=\operatorname{det}\left(\Omega_{1}(X, \bar{\beta})\right)^{\wedge}\left(\frac{1}{H}\right)
$$

where $\Omega_{1}$ is the AVC matrix, $\bar{\beta}$ are the priors, and H is the number of parameters to be estimated. The next step is to create a new design, and if the new design has a lower Derror, the new design is accepted. The process is repeated may times. In this manner, we also assume the usefulness of the orthogonal design in the remaining study.

## Remarks

The theory of stated choice experiment design is very extensive, and as such, it is not possible to include all aspects of the theory in this review.

### 2.10 Revealed Preference Techniques

In a survey we usually ask respondents to describe their actual reactions. Since this behavior is revealed, the data obtained from the retrospective questionnaires is called RP data. There are several possibilities as to how such data may be collected. One way is for the analyst to observe a market and note the alternatives as chosen and non-chosen. Another way may be by using some electronic device that records choices (Hensher, Rose and Greene, 2005). Alternatively, a questionnaire survey may be used. This type of collection may include information on simple socio-demographic (SDC) characteristics of the decision makers.

This method of data collection has certain limitations to collecting data only on currently existing alternatives. Whichever collection method of RP data is used, the analyst fails to collect information in the non-chosen alternatives as in SP methods. In this research study, the probability of failure among new transit modes, after a new transit mode is introduced, is likely to be of little benefit to the analyst. As an aside, RP collection data can be very costly in terms of both time and money spent (Hensher, Rose and Greene,
2005). In the figures below we graphically present the difference between the two types of techniques: RP (in Figure 2-2) and SP (in Figure 2-3).


Figure 2-2 Revealed Preference data

RP methods uncover estimates of the value of non-market goods by using evidence on how people behave in the face of real choices.

The two most common RP methods are:

- The Hedonic Pricing method, which involves examining people's purchasing decisions in markets related to the non-market good in question and
- The travel cost method, which involves observing costs incurred in the nonmarket good in question

One thing to remember with this type of data is the location where to distribute the questionnaire.

## Hypothetical behavior



Figure 2-3 Stated Preference data

### 2.11 Comparison of Stated Preference versus Revealed Preference

In this section we summarize the key differences between SP and RP Techniques (Louviere et al., 2000).

- RP data are more expensive compared to SP data
- SP methods are widely used and researched
- Suffer from hypothetical bias
- RP data depict the world as it is now
- RP data includes only existing alternatives as observables; which implies that existing absolute attribute levels and correlations between attributes will be in any model estimated from such data
- RP data have a high reliability and face validity since these choices are made by individuals who committed their actual resources to make the choices possible
- RP surveys yield one observation per respondent at each observation point
- SP data describe hypothetically or virtual decision contexts
- SP data control relationships between attributes which permit mapping of utility functions
- SP can include existing and/or proposed and/or generic choice alternatives (unbranded or unlabeled)
- SP surveys usually yield multiple observations per respondent at each observation point

The characteristics of RP and SP data are summarized in Table 2-1 (Sanko, 2001)
Table 2-1 RP and SP characteristics

|  | RP DATA | SP DATA |
| :---: | :---: | :---: |
| Preference Information | - The result of actual behavior <br> - Consistent with the behavior in real market <br> - We can get 'choice' as a result | - Expression under the hypothetical situation <br> - Possibility of inconsistent with the behavior in real market <br> - We can get 'ranking', 'rating', 'choice' etc |
| Alternatives | Only existing alternatives | Existing and non-existing alternatives |
| Attributes | - Measurement error <br> - Limited range of attributes' levels <br> - Possibility of collinearity among attributes | - No measurement error <br> - Extensibility of the range of attributes' levels <br> - Controlability of the collinearity among attributes |
| Choice set | Non-clear | Clear |
| Number of Responses | One response per respondent | One or more response(s) per respondent |

### 2.12 Rationale for Combining Actual Travel Data and Choice Experiment Data

Methods for analyzing mode choice are categorized as revealed preference or indirect methods and stated preference or direct methods. In Section 2.11 we discussed strengths and weaknesses of RP and SP data sources. In this section we present a very practical way of dealing with insufficient variation in explanatory attributes within one data source. Relatively recent developments in the literature have shown that combining observed and hypothetical behavior data can provide complementary information about preference structure and allow for improved statistical efficiency over the use of either method separately (Mitchell and Carson, 1989). The process of pooling RP and SP data and estimating a model from the pooled data is called data enrichment (Louviere et al, 2000). The "data enrichment" idea was originally proposed by Morikawa (1989) and was
illustrated later by the work of Ben-Akiva and Morikawa (1990), Ben-Akiva et al. (1991), Bradley and Daly (1994), Hensher and Bradley (1993) and others. Recent research indicated that combining the two types of data builds on the strengths and diminishes the drawbacks of each method.

Combining the two data sources, therefore, poses significant challenge for the analyst in terms of how to handle RP data. RP data is often collected only for the chosen alternative. Since discrete choice modelling requires at least two alternatives for a choice, the lack of information on the non-chosen alternatives within the RP data is a serious issue. Since it is not always possible to gather this kind of information from the decisionmakers, Hensher et al. (2007) proposes four solutions, two of which are presented in this section. The other two approaches require more information from the decision maker which is not always collected as part of an RP survey. Thus, we only present the first two. The first approach the authors suggest is to use the average of the attribute levels of each observed alternative and substitute these averages (or medians for qualitative attributes) as the values for the attribute levels of the non chosen alternatives for those who did not choose them. This is an easy way of generating data on the non-chosen alternatives. However, this approach reduces the variance of attribute-level distribution (Hensher, Rose and Greene, 2005). The second approach Hensher et al. (2007) propose is to randomly match the non-chosen alternatives attribute levels to specific decision makers through a matching of sociodemographic characteristics.

The advantages of combining RP and SP data as described by Ben-Akiva (1994) are listed below:

1. Efficiency: joint estimation of preference (or attribute importance) parametersfrom all of the available data;
2. Bias correction: explicit response models for SP data, which include both preference parameters and bias parameters; and
3. Identification: estimation of preferences for new products or services and for new attributes or attribute levels that are not identifiable from RP data.

So far, many applications are implemented, and the usefulness of this method is generally accepted.

### 2.13 Summary

The nature of the problem of altered travel patterns during Metro closures requires the collection of large data sets. We use both SP and RP techniques to assess user preferences during closures.

In the following chapters, we describe the econometric methods for estimating the parameters that affect travel pattern during disruptions using SP and RP data. In Chapters 5 and 6, we describe the RP experiment and the SP questionnaire we used and their results. In Chapter 7, we combine in our survey collection process RP and SP data sources so as to promote the strengths of both and minimize the disadvantages of each method.

## 3. Theoretical Framework

### 3.1 Introduction

In this chapter, an introduction of discrete choice models and random utility models will be presented, giving an overview on the theoretical aspects and focusing on those models that will be used to reflect the a priori assumptions of the analyst as to what models affect the decision process of choice of mode during Metro disruptions. This is primarily based on Ben-Akiva and Lerman (1985). First, we model travel patterns during interrupted Metro operations as a sequence of choices on which alternative mode to use, so that discrete choice models represent a natural way to deal with this modeling assumption. We review three discrete choice models and their basic theory to relate, by means of a mathematical function, the choice of mode during a Metro closure with the characteristics of the population (age, income, gender, etc.) and the transportation system (travel time, cost, etc).

Many transport modeling issues can be viewed as the result of a route choice, choice of a transportation mode, choice of the destination etc. Therefore, modeling and predicting individual choice has been widely used by practitioners and researchers. In this context, Random Utility Theory and its corresponding models, is widely used (see Domencich and McFadden, 1975) with numerous applications in transportation science (Ben-Akiva and Lerman, 1985, Ben Akiva and Bierlaire, 1999; Ben-Akiva et al., 1984, Cascetta et al.,1992). These models are based on the assumption that individuals belong to a homogenous population, follow a rational behavior pattern, and that they always select the alternatives that maximize their personal utility. The individual's choice set is predetermined consisting of a certain set of alternatives and a set of vectors of measured attributes of the individuals and the alternatives (Ortuzar, 1994). Consequently, each alternative has an associated utility that mathematically expresses the individual's preference. This utility is composed of a measurable, systematic or deterministic part, that varies across alternative characteristics and across individuals, and is a function of the measured attributes, and of a random or stochastic part that represents the uncertainty (a fuzzy set extension has also been suggested to handle it, namely by Lotan, 1992 and Bierlaire, Burton and Lotan, 1993). This uncertainty comes, for instance, from unobserved or unavailable characteristics, taste variation among individuals or, simply, measurement errors. The reader is referred to Ben-Akiva and Lerman (1985) for details about the nature of this uncertainty.

In this chapter for the statistical analysis of the data/questionnaires we use discrete choice models that have been used to model choices among alternative modes. The Multinomial Logit (MNL), Multinomial Probit (MNP) and Heteroksedastic Extreme Value Logit (HEV) models are estimated in this study (Washington et al. 2010). Model estimation of choice data was done by means of NLOGIT software package (v5.0).

The discussion in this chapter is structured as follows. After a brief review of the main concepts of discrete choice models in Section 3.2, we give an overview of the Logit Model in 3.3, of the MNL in 3.4 and MNP in 3.5 and describe the different model specifications. This is followed in section 3.6 by a discussion of the HEV model and Nested Logit in 3.7. We also discuss cross elasticities and tests (Likelihood Ratio Test) for each model. The chapter closes with a summary in Section 3.8.

### 3.2 Basic Concepts of Discrete Choice Models

Within the context of disruptions in Metro systems, transport planners need to devise appropriate strategic planning tools to improve public transport. In order to analyze traveler behavior and altered travel patterns we need to undertake a mode choice analysis. Such analysis allows transport planners to forecast which transport mode will be used in the case of a Metro closure. Models can be used to predict how changes in a transportation system will affect the individual traveler's choice. The outcome models will provide the relationship between the probability of choosing an alternative and the attributes or benefits that characterize the alternative.

The framework for a discrete choice model can be presented by a set of general assumptions as follows (Ben-Akiva and Bierlaire, 1999):

- Decision maker including his socio-economic characteristics
- The set of Alternatives (choice set)
- Attributes of alternatives
- Decision rules

By decision-maker we refer to either a group of people or a single individual. When referring to a group of people who share some common characteristics with term "individual" we ignore all internal interactions within the group. To explain heterogeneity
within this group the researcher collects socio-economic variables of age, gender, income and education (Ben-Akiva and Bierlaire, 1999).

The specification of the available attributes presented to the respondents is a complex procedure and requires knowledge not only of the available travel modes but also of the non-available. In this procedure it is required to use deterministic criteria of alternative availability (i.e. the possession of driving license). The attributes presented to the individuals describe the alternatives in terms of attractiveness and can be either categorical or numerical or qualitative. They may also be expressed as a function of measurable data. Finally, the decision-maker needs to decide upon the theory to use to evaluate the attributes of the alternatives and determine a choice. This is called the decision rule. Most analysts use intensively random utility models in travel behavior analysis and in econometrics (Ben-Akiva and Bierlaire, 1999).

In this section, we briefly look at some of the concepts that the theory of discrete choice modeling is based on. In a discrete choice experiment, a decision maker $n$ chooses from a choice set $C_{n}$, made up of a finite number of mutually exclusive alternatives and has no effect on the choice process undertaken by the decision-maker. Each alternative $i=1, \ldots I$ in the choice set is characterized by a utility $U_{i n}$, which is specific to decision-maker $n$, due to variations in attributes of the individuals and the attributes of the alternative (Hess, 2005).

According to Utility maximization theory, there is a mathematical function $U_{\text {in }}$ called a utility function, whose numerical value depends on attributes of the available options and the individual. Based on this theory the individual will choose alternative $i$ only if $U_{i n}>U_{j n}, \forall j \neq i$, and $i, j \in C_{n}$.

However, this theory yields a simple model of decision rule that makes deterministic prediction of travel choices but does not treat the variations in travel behavior. In other words this theory does not take into account the uncertainty into the predicted choices. The complexity of human behavior suggests that the decision rule should include a probabilistic dimension in order to tackle the issue of the uncertainty.

The inclusion of a deterministic part to capture the uncertainty in the utility function leads to the Random Utility Model (RUM) which is the most common theoretical basis of discrete choice model (Ben-Akiva and Bierlaire, 1999). These models give probabilities
that each available mode will be chosen. The probability of an individual $n$ choosing alternative $i$ is given by equation (1).

$$
\begin{equation*}
P_{i n}=P\left(V_{i n}+\varepsilon_{i n}>V_{j n}+\varepsilon_{j n}\right)=P\left(\varepsilon_{j n}-\varepsilon_{i n}<V_{i n}-V_{j n}\right), \forall i, j \in C_{n}, \text { and } i \neq j \tag{1}
\end{equation*}
$$

Traditionally, decision makers choose among a set of alternatives such that their utility (satisfaction) is maximized subject to the prices of the alternatives and an income constraint (see Nicholson, 1978). Disaggregate models which are modern approaches to mode choice modeling are based on the utility maximization theory.

In general, the utility specification can be given as,
$U_{\text {in }}=V_{\text {in }}+\varepsilon_{\text {in }}$
With $i=1, \ldots, I$ and $n=1, \ldots, N$. Equation (2) suggests that the random utility specification $U_{\text {in }}$ of alternative $i$ to individual $n$, corresponding to the relative attractiveness of the option, may be treated as a random variable consisting of the sum of an observable utility component $V_{\text {in }}$ (the deterministic part of the utility) plus an unobserved random component $\varepsilon_{i n}$ capturing the uncertainty with zero mean and a normal distribution (McFadden 1974). The unobserved random component represents the uncertainty associated with the expected utility of an alternative. The $\varepsilon_{i n}$ includes idiosyncrasies and taste variations, combined with measurement or observation error. The error term allows for two important cases:

- In the case of two different persons with the same measured attributes who face the same choice set, can make different decisions
- Some decision-makers do not select the best alternative

We can write the deterministic part of the utility that individual $n$ is associating with alternative $i$ as:

$$
\begin{equation*}
V_{i n}=V_{i n}\left(x_{i n}\right) \tag{3}
\end{equation*}
$$

Where $x_{i n}$ is a vector containing all attributes, both of individual $n$ and alternative $i$. The function is commonly assumed to be linear in the parameters and is denoted as follows:
$V_{i n}\left(x_{i n}\right)=\beta_{1} x_{i n}(1)+\beta_{2} x_{i n}(2)+\cdots+\beta_{I} x_{i n}(I)=\sum_{k=1}^{I} \beta_{\kappa} x_{i n}(\kappa)$

Where parameters $\beta_{1}, \beta_{2}, \ldots, \beta_{I}$ are the parameters to be estimated and $k(k=1, \ldots K)$ is the total number of parameters and $\beta_{0 i}$ is a parameter not associated with any of the observed and measured attributes, called the alternative-specific constant. Parameters $\beta$ are generally estimated using maximum likelihood method. In MNL, MNP and in multinomial models with choice-fixed predictors in general, the coefficients do the same thing: they describe the relative probability of a choice to a base choice. Therefore if there are $n$ choices, MNL and MNP will provide $n-1$ sets of coefficients, setting the coefficients for the choice all equal to zero.

The choice model is then derived by making a suitable assumption on the distribution of the random term. The vector $\varepsilon_{n}=\left(\varepsilon_{1 n}, \ldots, \varepsilon_{\text {In }}\right)$ can be a vector of joint density $f\left(\varepsilon_{n}\right)$, zero mean and covariance matrix $\Omega$. Hence, the probability of alternative $i$ in equation (1) is the cumulative distribution of the random term $\varepsilon_{j n}-\varepsilon_{i n}$ and can be described in equation (5):
$P_{\text {in }}=\int_{\varepsilon_{n}} I\left(\varepsilon_{j n}-\varepsilon_{i n}<V_{i n}-V_{j n}, \forall i \neq j\right) f \varepsilon_{n} d \varepsilon_{n}$
Where $\mathrm{I}($.$) is the indicator function which equals 1$ if the term inside the brackets is true and 0 otherwise (Hess, 2005).

Traditionally, decision makers choose among a set of alternatives such that their utility (satisfaction) is maximized subject to the prices of the alternatives and an income constraint (see Nicholson, 1978). Disaggregate models which are modern approaches to mode choice modeling are based on the utility maximization theory.

For further details see Ben-Akiva and Lerman (1985), Hensher and Johnson (1981) or Ortuzar and Wilumsen (1994).

The mathematical framework for Logit Models is discussed in detail in Washington et al. (2010).

In the next sections, an introduction of discrete choice models will be presented and the relevance of these models with the problem of transportation disruptions and travel patterns. Discrete choice models have been developed for examining the behavior of individual decision makers who can be described as facing a choice set which is finite.

### 3.3 Logit Model

Many different probabilistic choice models can be derived by making different assumptions about the distribution of the random part of the utility which is referred to as the stochastic part of the utility. In the case of Binomial choice models the most common models found in practice are: the logit and the probit. The logit model assumes a logistic distribution of errors, and the probit assumes a normal distribution of errors. For example a Gumbel distribution gives rise to the conditional or Multinomial Logit Model and a bivariate normal distribution yields the binary probit model or Probit models arise when the disturbance terms $\varepsilon$ in equation (2) are assumed to be normally distributed.

The probability for alternative $i$ is given in equation (1).

Binary models are those models which consider two discrete outcomes and multinomial models are those which consider three or more discrete outcomes.

In MNL models, the random components $\varepsilon_{i n}$ are extreme value type I (Gumbel distributed) and are identically and independently distributed across alternatives. There has been concern about its inherent property of Independence from Irrelevant alternatives (the well known IIA) (Munizaga et al., 2000). In the MNL model, the error terms are supposed to be independent and homoskedastic (Munizaga et al. 2000), making it restrictive for practical use (this is the well known IIA property). Many applications in marketing, transport and the environment use the simple MNL model since it can be straightforwardly used to analyze SP or RP survey observations (Louviere et al. 2000; Munizaga et al. 2000). Because the coefficients of multinomial logistic models are generally difficult to interpret directly, marginal effects for each variable are computed.

The MNL's assumption of homoskedasticity is limited because it cannot model taste variation among respondents. It also exhibits restrictive substitution patterns due to the IIA property. Unlike the MNL, the MNP offers a highly desirable flexibility in substitution among alternatives that the MNL fails to process (McFadden 1974).

The standard equation for the utility of an alternative $i$ is given in equation (6).
$P_{\text {in }}=P_{r}\left[\varepsilon_{j n}-\varepsilon_{i n} \leq V_{i n}-V_{j n} \forall j \in C_{n}\right]=$
$\int_{-\infty}^{V_{i n}-V_{1 n}} \int_{-\infty}^{V_{i n}-V_{2 n}} \ldots \int_{-\infty}^{V_{i n-} V_{j n}} N\left(0, \Sigma_{\varepsilon-\varepsilon_{l}}\right) d \varepsilon, \quad \forall i \in C_{n}$

Where $N\left(0, \Sigma_{\varepsilon-\varepsilon_{l}}\right)$ is a multivariate Normal density function with zero means and covariance matrix $\Sigma_{\varepsilon-\varepsilon_{l}}$ and J is the number of options in the set $C_{n}$ (Munizaga et al., 2000). The complexity of this integral requires simulation to solve it.

If the error terms are independent and identically Gumbel distributed with location parameter 0 and scale parameter $\mu>0$, the probability that a given individual choose alternative $i$ within $C$ is given by equation (7):
$P_{i n}=\frac{e^{\mu V_{i n}}}{\sum_{k \in C} e^{\mu V_{k}}}$
Where $\mu$ is a parameter related to the variance $\sigma^{2}$ of the error term $\mu=\frac{\pi}{\sigma \sqrt{6}}$
The MNL expresses the probability that a specific alternative is chosen is the exponent of the utility of the chosen alternative divided by the exponent of the sum of all alternatives (chosen and not chosen). The predicted probabilities are bounded by zero and one.

### 3.4 Multinomial Logit Model

The MNL model is a general extension of the binomial choice model to more than two alternatives. There are several assumptions embedded in the estimation of MNL models:

- Linear in parameters restriction (for convenience of estimation)
- The disturbances are independently distributed
- The disturbances are identically distributed
- The disturbances are Gumbel distributed with location parameter $n$ and a scale parameter $\mu>0$

The Multinomial Logit Model is derived from the assumption that the error terms of the utility functions are independent and identically Gumbel distributed (or type I extreme value). The probability density function of the extreme value type I distribution is:
$f(\varepsilon)=\mu e^{-\mu\left(\varepsilon_{i n}-n\right)} \exp \left[-e^{-\mu\left(\varepsilon_{i n}-n\right)}\right], \mu>0$
with corresponding distribution function:
$F(\varepsilon)=\exp \left[-e^{-\mu\left(\varepsilon_{\text {in }}-n\right)}\right], \mu>0$
where n is a location parameter (mode) and $\mu$ is a strictly positive scale parameter. The mean of this distribution is $n+\gamma / \mu$
where
$\gamma=\lim _{\kappa \rightarrow \infty} \sum_{i=1}^{k} \ln (k) \cong 0.5772$
is the Euler constant. The variance of the distribution is $\pi^{2} / 6 \mu^{2}$.
The MNL model belongs to the family of the Generalised Extreme Value (GEV) models which is a set of closed form discrete choice models that are all based on the use of the extreme value distribution. The MNL model which was at first referred as the conditional logit is a general extension of the binomial choice model to more than two alternatives. There are several assumptions embedded in the estimation of MNL models. Numerous approaches exist leading to the derivation of the logit choice probabilities (Ben-Akiva \& Lerman, 1985; Domenich and McFadden, 1975; Train, 2003).

The MNL choice probability for alternative $i$ and decision-maker $n$ is given by:
$P_{n}(i)=P_{i n}=\frac{e^{\mu V_{i n}}}{\sum_{j=1}^{I} e^{\mu V_{j n}}}, j=1, \ldots, i, \ldots, I \in C_{n} \forall i \neq j$

Setting $\mu=1$ the above equation becomes
$P_{i n}=\frac{e^{V_{i n}}}{\sum_{j=1}^{J} e^{V_{j n}}}, j=1, \ldots, i, \ldots, I \in C_{n} \forall i \neq j$
which is the standard Multinomial Logit formulation. It is referred to as a closed-form model because applications do not require any further application. Eq [12] above states that the probability of an individual choosing alternative $i$ out of the set of $I$ alternatives is equal to the ratio of the (exponential of the) observed utility index for alternative $i$ to the sum of the exponentials of the observed utility indices for all $I$ alternatives, including the $i$ ith alternative (Hensher Rose and Greene, 2005).

For the estimation of the beta coefficients in the utility functions we use the maximum $\log$ likelihood function. The $\log$ likelihood function for a sample of choice situations 1 , N , together with the corresponding values of $x_{i n}$ is:
$L L=\sum_{n=1}^{N}\left(\sum_{i=1}^{I} \delta_{\text {in }}\left[V_{i n}-\ln \sum_{\forall I} \exp \left(V_{i n}\right)\right]\right)$
where $I$ is the total number of outcomes and $\delta$ is defined as being equal to 1 (Washington et al., 2010). To estimate of the utility parameters of the utility expressions we use the Maximum Likelihood Estimation (MLE). The maximum likelihood estimator is the value of parameter which causes the likelihood function to be a maximum (Louviere et al., 2000). As likelihood function falls between 0 and 1, the log likelihood function is negative. The smallest negative value of the log-likelihood function is the maximum to the log-likelihood function.

Where the fact that the choice probability no longer involves the error term $\varepsilon_{n}$ means that the model can be estimated and applied without the use of simulation. The measure of Log likelihood is not measure of "fit".

The assumption of independently and identically distributed (IID) error terms in MNL leads to its famous IIA property. IID implies that the variances associated with the random components of the utilities of each alternative are identical and not correlated between all pairs of alternatives. In the case of 3 alternatives the variance-covariance matrix can be written as:

$$
\left[\begin{array}{ccc}
\sigma^{2} & 0 & 0  \tag{14}\\
0 & \sigma^{2} & 0 \\
0 & 0 & \sigma^{2}
\end{array}\right]
$$

### 3.4.1 MNL Limitations

In the following section we describe three important characteristics of the MNL model which limit its flexibility and induce the use of more sophisticated techniques:

These are:

1. Independence from irrelevant alternatives,
2. Deterministic taste variations,
3. Homoskedasticity.

## Independence from Irrelevant Alternatives Property (IIA)

An important property of the Multinomial logit model which governs MNL's behavior is the independence from Irrelevant Alternatives. This can be explained as: the ratio of the

MNL choice probabilities of any two alternatives $i$ and $j$ is independent of the attributes or even existence of other alternatives from the choice set. Let $\varepsilon_{i n} \varepsilon_{j n}$ denote the unobserved part of the utilities for alternative $\underline{i}$ and $j(i \neq j)$ in the choice set. This can be directly derived from equation (15):
$\frac{P_{i n}}{P_{j n}}=\frac{e^{\mu V_{i n}}}{e^{\mu V_{j n}}}$

So the relative probability that an individual chooses choice $i$ over choice $j$ is unaffected by the systematic utilities of any other alternatives. Any changes in the probability of a given alternative draw equally from the probabilities of all the other alternatives in the choice set, which leads to the conclusion that cross-elasticities are equal.

While there are many cases where the ILA property is not acceptable (i.e. Ben-Akiva \& Lerman, 1985) and the MNL model should not be used, there are however cases where IIA is a valid assumption, namely in those cases where the single alternatives are virtually unrelated, or when the relationship (closeness) between any two alternatives is the same for all pairs of alternatives (Hess, 2005). The limitation of the IIA assumption is often illustrated by the red/blue bus in the modal choice context.

Hence is important to test the validity of the IIA assumption to avoid fitting an MNL model to a choice set that violates IIA. Hess (2005) also suggests careful specification of the observed utility function to avoid correlation in the unobserved part of utility between alternatives.

The behavior of individuals varies across the population. A MNL model is an appropriate model in the case where the systematic component of utility accounts for heterogeneity (taste variations) across individuals. In general, models with many socio-economic variables have a better chance of not violating IIA ${ }^{1}$.

## Deterministic Taste Variations

Logit models can by construction handle just only systematic (deterministic) taste variations, but not random taste variation. For example the effect of a change in bus ticket is often influenced by the individual's income. Though some travelers may exhibit the same socio-demographic characteristics they may value differently alternative values.

[^2]These random taste variations can only be modeled by using stochastic coefficients. This cannot be modeled by MNL models.

## Homoskedasticity

The third limitation, i.e., the homoskedasticity, is imposed by the assumption that the error terms are identically distributed. It means that all of them have the same scale parameter $\mu$. This fact implies that the variances are the same across the population. Let us assume that we have two different datasets and the utility for the first dataset is
$U_{i n}=V_{i n}+\varepsilon_{i n}$

And for the second dataset is
$U_{i m=} V_{i m}+\varepsilon_{i m}$
Homoskedasticity exists when $\operatorname{Var}\left(\varepsilon_{i n}\right)=\operatorname{Var}\left(\varepsilon_{i m}\right)$
Homoskedasticity in MNL models fails in two situations. When using two data sets from two sources, say one from RP survey and one from SP survey we cannot assume that the error variances are identical (Munizaga et al., 2000). Thus we need to allow for heteroskedasticity. Another issue arises when there is need to rank options in SP experiments when ranking options have high or low rank. Permain et al. (1991) argued that people may be more precise when ranking options that have either high or low rank and less precise with those that are intermediate. He also argues that the intermediate options are expected to have larger error variances.

To assess the individual parameter estimates we can use two other techniques: elasticities and marginal rate of substitution. By computing elasticities we measure the magnitude of the impact of specific variables on the outcome probabilities (Washington et al., 2010).

MNL model is insufficiently heterogenous; "...economists are often more interested in aggregate effects and regard heterogeneity as a statistical nuisance parameter problem which must be addressed but not emphasized. Econometricians frequently employ methods which do not allow for the estimation of individual level parameters" (Allenby and Rossi, 1999).

### 3.4.2 Disaggregate Direct Elasticities

The coefficients produced by a logit model can help the analyst understand the direction of the dependent variable $y$ and the statistical significance associated with the effect of changing an independent variable. Unfortunately, the coefficients cannot explain the magnitude of the effect of a change in $X_{k i}$ on the predicted probability. Hence, we need to calculate the marginal effects.

The direct point elasticity of traveler $i$ for parameter $k$ on alternative $a$ is computed from the partial derivative for each observation n :
$E_{x_{k i}}^{P(i)}=\frac{\partial P(i)}{\partial x_{k i}} * \frac{x_{k i}}{P(i)}=[1-P(i)] \beta_{k i} x_{k i}$
where $P(i)$ is the probability of outcome $i$ and $x_{k i}$ is the value of variable $k$ for outcome $i$.

Elasticity values measure the percent effect that a $1 \%$ change in $x_{i k}$ has for outcome $i$. In the case of indicator variables (variables that take on values 0 and 1 , such as the male indicator) we compute the pseudoelasticity which is given by the following equation:
$E_{x_{k i}}^{P(i)}=\frac{\exp \left[\Delta\left(\beta_{i} x_{i}\right)\right] \sum_{\forall I} \exp \left(\beta_{k i} x_{k i}\right)}{\exp \left[\Delta\left(\beta_{i x_{i}}\right)\right] \sum_{\forall I n} \exp \left(\beta_{k I} x_{k I}\right)+\sum_{\forall I \neq I n} \exp \left(\beta_{k I} X_{K I}\right)}-1$
where $I_{n}$ is the set of alternate outcomes with $x_{k}$ determining the outcome, and $I$ is the set of all possible outcomes.

### 3.4.3 Disaggregate Cross Elasticities

When we want to measure the effect of a change in attribute " $k$ " of alternative " $m$ " on the probability that the individual makes choice " j ", we compute the cross elasticities. The value of cross-elasticity can be evaluated as follows:
$E_{x_{k i}}^{P(i)}=-P(j) \beta_{k j} x_{k j}$
The cross elasticity in the equation (20) depends on variables associated with alternative $j$ and is independent of alternative $i$. Thus MNL cross elasticities are the same for all $i \neq j$. This is a consequence of the IID assumption in the model specification that all utilities are distributed about their means with independent and identically distributed distributions (IID). When we relax the IID assumption, the elasticity formula changes.

### 3.4.4 Willingness-to-Pay or Willingness-to-Accept

The amount of money an individual is willing to pay or accept to achieve some benefit from a specific action (in our case from a certain trip or route or mode chosen) is called Willingness to Pay (WTA) or Willingness to Accept (WTA). In Chapter 5 we devote a section to discuss the computation of WTP to obtain travel time savings.

### 3.4.5 Statistical Evaluation - Asymptotic t-tests

The parameter estimates obtained from an MNL analysis are subject to error. The amount of error is given by the standard error of the coefficient (Hensher, Rose and Greene, 2005). In linear regression analysis this test is usually performed via a t -test or F test. In MNL models this test is the Wald-statistic, both calculated and interpreted in the same manner as in the regression analysis. This test is used primarily to test whether a particular parameter in the model differs significantly from zero or some other constant. The test $t^{*}$, which is approximately $t$ distributed, is:
$\operatorname{Wald}\left(t^{*}\right)=\frac{\beta}{\text { S.E. }(\beta)}$

The critical levels for Wald t-statistic assuming a 95 percent confidence level (i.e alpha $=0.05)$ is 1.96 . If the absolute value of the Wald-test statistic given in the output is greater than the critical Wald value, the analyst may conclude that the relevant attribute is statistically significant (Hensher, Rose \& Greene, 2005).

Where S.E. $(\beta)$ is the standard error of the parameter. For a parameter $\beta_{k}$ which is normally distributed with variance $\sigma_{k}$, the hypotheses need to be tested such as:

$$
\begin{equation*}
H_{0}: \beta_{k}=\beta_{k}^{*} \tag{23}
\end{equation*}
$$

$H_{0}: \beta_{k} \neq \beta_{k}^{*}$

Where $H_{0}$ denotes the null hypothesis, $H_{1}$ denotes the alternative hypothesis, and $\beta_{k}^{*}$ denotes the known constant. If $\beta_{N}$ is a normally distributed vector with K entries $\beta_{\mathrm{N} w}$, and N denotes the sample size, then statistic $\frac{\beta_{N K}}{\sigma_{N K}}$ is generally distributed with $\mathrm{N}-\mathrm{K}$ degrees of freedom. For a given significance level $\alpha$, the critical region (i.e. the values of $\beta_{N K}$ for which $H_{0}$ is rejected). For this statistic can be constructed as:

$$
\begin{equation*}
P_{r}\left[t_{N-K, a / 2} \leq \frac{\beta_{N K}-\beta_{*}}{\sigma_{N K}} \leq t_{N-K, 1-\alpha / 2}\right]=1-\alpha \tag{25}
\end{equation*}
$$

Where $t_{N-K, a / 2}$ and $t_{N-K, 1-\alpha / 2}$ denote the $\frac{a}{2}$ and $1-\frac{a}{2}$ cumulates of the t distribution with $N-K$ degrees of freedom respectively. This yields a critical region of $\mid \beta_{N K}-$ $\beta * \geq t N-K, a / 2 \sigma N K$

If the estimated parameter belongs to this region, the null hypothesis is rejected.

Washington et al. (2010) argue that the use of t statistics is not strictly correct because the MNL model is derived from an extreme value distribution. A more general and appropriate test to assess the statistical significance of individual parameters in an MNL model is the likelihood ratio test.

### 3.4.6 Likelihood Ratio Test

A likelihood ratio test is a very general test that is often used to assess the significance of individual parameters, evaluating overall significance of individual parameters and examining the appropriateness of estimating separate parameters for the same variable in different outcome functions.

Let $L^{U}$ and $L^{R}$ denote the value of the $\log$ likelihood (LL) function at convergence (at its maximum) for the "unrestricted" (the base model-the largest LL value) and the "restricted" (the estimated model-the smallest LL value) models. This statistic is $X^{2}$ distributed with degrees of freedom equal to the difference $K^{U}-K^{R}$, which is the number of independent restrictions imposed on the parameters in computing LR.

The test statistic for the null hypothesis that the restrictions are true is:

$$
\begin{equation*}
X^{2}=-2\left(L^{U}-L^{R}\right) \tag{26}
\end{equation*}
$$

Is asymptotically $X^{2}$ distributed with $\left(K^{U}-K^{R}\right)$ degrees of freedom (difference between the number of parameters estimated between the two models). If this value exceeds the critical Chi-square value with appropriate degrees of freedom at a certain significance level, then the null hypothesis will be rejected because the specified model is no better than the base comparison model.

To perform the LRT test we need to run the model twice, one with the explanatory variables and one without them. To test the significance of individual variables added we need to compare the improvement in likelihoods as individual variables are added.

### 3.4.7 Goodness of Fit

Finally, it is often to measure the overall model fit by measuring the likelihood ratio index (rho-squared). The $p s e u d o-\rho^{2}$ statistic is:
$\rho^{2}=1-\frac{L(\beta)}{L(0)}$
where $L(B)$ is the $\log$ likelihood value at convergence with the estimated parameter and $\mathrm{L}(0)$ is the value when all parameters are set to zero (initial log likelihood). The generation of the pseudo $-\rho^{2}$ statistic associated with choice models is not analogous to the $\rho^{2}$ statistic of the linear regression (Hensher, et al, 2007) and this is because the underlying choice analysis is non linear in MNL model. This index measures how well the model with the estimated parameters performs compared with a model in which all parameters are zero which is equivalent to having no model at all.

There are no general guidelines for when the $\rho^{2}$ is sufficiently high. Domencich and McFadden (1975) showed that there exists a direct empirical relationship between pseudo $-\rho^{2}$ and $\rho^{2}$ statistic of the linear regression (Figure 3-1).


Figure 3-1 Mapping the pseudo $\boldsymbol{\rho}^{\mathbf{2}}$ to the linear $\boldsymbol{\rho}^{\mathbf{2}}$

To compare two models estimated on the same data and with the same set of alternatives, is usually valid to say that the model with higher $\varrho^{2}$ fits the data better. The disadvantage of $\rho^{2}$ statistic is that it will always improve with the addition of new parameters even though they are insignificant. A corrected $\rho^{2}$ statistic is:

$$
\begin{equation*}
\rho^{2}=1-\frac{L(\beta)-k}{L(0)} \tag{28}
\end{equation*}
$$

Where $k$ is the number of parameters estimated in the model.

### 3.5 Multinomial Probit Model

The main alternative to Generalised Extreme Value-based model structures is the Multinomial Probit (MNP) model. Probit models arise when the disturbance (error) terms in the utility function in equation (2) (analogous to the hybrid logit model) are normally distributed with zero mean and the error terms may be correlated.

Unfortunately, the choice function of MNP cannot be easily written in a closed form, except for the case of two alternatives (Daganzo, 1979). The utility function of MNP model is defined by:
$U_{i n}=\beta_{i} x_{i n}+\varepsilon_{i n}$
If we assume that $\varepsilon_{i n} \mid x_{i n} \sim$ Multivariate Normal $N[0, \Sigma]$
The advantage of MNP over MNL is that MNP does not assume IIA and hence taste variation can be incorporated in probit models. Thus it allows for correlation across choices and allows for heteroskedasticity. It does however have some restrictions to its use. The disadvantage is far more computationally intensive. The probability of choosing alternative 1 is the probability that $U_{i 1}$ is the highest evaluation:

The choice probability for a probit model is:
$P_{n i}=P\left(V_{n i}+\varepsilon_{n i}>\mid V_{n j}+\varepsilon_{n j} \forall j \neq i\right) \mid=$
$\int_{\varepsilon_{n}} I\left(V_{n i}+\varepsilon_{n i}>V_{n j}+\varepsilon_{n j}<\forall j\right.$

$$
\begin{equation*}
\neq i) \varphi\left(\varepsilon_{n}\right) d_{n} \tag{30}
\end{equation*}
$$

Where I is the indicator function and $\varphi\left(\varepsilon_{n}\right)$ is the density function of a typical normal distribution described by:

$$
\begin{equation*}
\varphi\left(\varepsilon_{n}\right)=\frac{1}{\sqrt{2 \pi} \sqrt{\left|\Sigma_{n}\right|}} \exp ^{-\frac{1}{2} \varepsilon_{n}^{\prime} \Sigma_{n}^{-1} \varepsilon_{n}} \tag{31}
\end{equation*}
$$

Unlike with standard logit models, this integral does not have a closed form solution and must be evaluated numerically through simulation.

And the covariance matrix is

$$
\sum=\left(\begin{array}{ccc}
\sigma_{1}^{2} & \cdots & \sigma_{1}^{n} \\
\vdots & \ddots & \vdots \\
\sigma_{1 n} & \cdots & \sigma_{n}^{2}
\end{array}\right)
$$

The parameter estimates are typically estimated by Maximum likelihood methods. To estimate the effect of an independent variable we estimate the marginal effects.

In a linear model $y=\beta_{0}+\beta_{1} x_{1}+\cdots+\beta_{n} x_{n}$
In the probit model $y=\varphi\left(\beta_{0}+\beta_{1} x_{1}+\cdots+\beta_{n} x_{n}\right)$
To find the partial marginal effect of the choice probability $\operatorname{Prob}(y=1 \mid x)$, we need to base our estimations on the estimation of partial deviation.
$\frac{\partial \operatorname{Prob}(y=1 \mid x)}{\partial X_{i}}=\beta_{i} \varphi\left(\beta_{0}+\beta_{1} x_{1}+\cdots+\beta_{n} x_{n}\right)$
In this case the probability density function is a multivariate normal distribution, a notoriously difficult function to integrate.

Binary probit models are under-specified in that we cannot simultaneously estimate the coefficients using this normalization. In effect we are dividing all the coefficients by the standard deviation of the errors. But then, we are really estimating $\beta / \sigma$ rather than $\beta$, so we cannot trust the direct point estimates from a binary probit model. Multinomial
probit models make a similar normalization: they constrain one of the variances in the differenced variance-covariance matrix ${ }^{2}$.

Until the 1990's researchers rarely used the MNP due to computational difficulties in estimating the maximum likelihood (MLE) (Culloch and Rossi 1993). The probit model assumes a normal distribution of errors. This model is not easy to estimate for more than 4 or 5 choices.

In the case of MNL model, the maximum likelihood function may be written as:
$L\left(\theta \mid S_{1}, S_{2}, ., S_{T}\right)=\prod_{t=1}^{T} P_{S}\left(S_{t} \mid \theta\right)$

Where $\theta$ is the parameter to be estimated, and $S_{t}$ is one of the many possible samples the analyst may take from the total population of decision makers. Taking the $\log$ of the above equation (35) we obtain:
$\operatorname{Ln}(L(\theta))=L *(\theta)=\ln \left(\prod_{t=1}^{T} P_{S_{t}}\left(s_{t} \mid \theta\right)\right)=\sum_{t=1}^{T} \ln \left(P_{S_{t}}\left(S_{t} \mid \theta\right)\right)$
LL functions closer to zero represent best model fits. The likelihood functions for Multinomial Logit and multinomial probit differ only in the formulation of the choice probabilities. Let (individual i):
$\lambda_{i j}= \begin{cases}1, & \text { if } y_{i}=j \\ 0, & \text { if } y_{i} \neq j\end{cases}$

Then the likelihood function is
$\mathrm{L}=\prod_{i=1}^{N} \prod_{j=1}^{M} P\left(y_{i}=j\right)^{\lambda_{i j}}$
which is maximized with respect to the coefficients. For the logit models, the choice probability inside the double-product is straight forward, so these models are computed quickly. But for MNP this function is extremely complex. There are simulation methods to approximate the maximum likelihood values for MNP, but even these take time. For MNP, standard maximum likelihood estimation of the likelihood function will fail to

[^3]converge. NLOGIT and other statistical packages use instead simulated maximum likelihood techniques. The choice probabilities are estimated using a technique involving random draws and Monte Carlo estimation. The Monte Carlo estimation method has been suggested by Manski and Lerman (1977). It consists in evaluating the MNP probability function by performing experiments with random numbers (Daganzo, 1979).

But what happens if there is heteroskedasticity in the sample? In the context of travelers one might expect the standard deviation to vary systematically among respondents. In this case, if a probit model is used but the error terms are heterosedastic, the $\beta$ parameter estimates will be biased. One approach to treat heteroskedasticity is to estimate a heteroskedastic logit (or probit) model.

Estimation of MNP models is now possible in a reasonable time using more advanced computational techniques. The main problem is due to the lack of an analytical expression for the probability function of a variable which is Multivariate Normal distributed.

### 3.6 Heteroskedastic Extreme Value Model

To take into account the heteroskedasticity between option, a new model the Heteroskedastic Extreme Value Model (HEV) has been developed and applied (Bhat, 1995; Hensher, 1996). HEV is an important simplification of multinomial probit models. Unlike the MNP, HEV assumes that the utility of alternative $i$ for each individual $j$ has heteroskedastic random components, where the cumulative distribution function of the Gumbel distributed is given $\mathrm{by}^{3}$ :
$F\left(\varepsilon_{i j}\right)=\exp \left\{-e^{-\varepsilon_{i j} \theta_{j}}\right\}$,
where $\varepsilon_{\mathrm{ij}}$ is independently extreme value distributed with variance $\frac{1}{6} \frac{\pi^{2}}{\theta_{j}^{2}}$. There is no correlation in unobserved factors over alternatives. In order to consider heteroskedasticity among observations we used the HEV Model. A detailed description of HEV model is available in Zeng (2000) and Ben-Akiva and Lerman (1985). HEV model (a) overcomes the "independence of irrelevant alternatives" (IIA) restriction of the commonly used logit model, (b) permits more flexibility in cross-elasticity structure than the nested logit model; and (c) is simple, intuitive and computationally less

[^4]burdensome compared to the multinomial probit model. The Multinomial Logit model imposes the restriction of equal cross-elasticities due to a change in an attribute affecting only the utility of an alternative $i$ for all alternatives $j \neq i$. Stopher et al. (in Bhat, 1995; 1981) state that this property of equal proportionate change of unchanged modes is unlikely to represent actual choice behavior in many situations.

The random utility of alternative $i U_{i}$, for an individual in random utility models takes the form
$U_{i}=V_{i}+\varepsilon_{i}$
where $V_{i}$ is the systematic component of the utility of alternative $i$. Let C be the set of alternatives available to the individual. In this model the random components in the utilities of the different alternatives are assumed to have a type I extreme value distribution and to be independent, but not identically distributed. The random components are also assumed to have a location parameter equal to zero and a scale parameter equal to $\theta i$ for the ith alternative. Thus the probability density function and the cumulative distribution function of the random error term for the ith alternative are given by equations (41) and (42):
$f\left(\varepsilon_{i}\right)=\frac{1}{\theta_{\imath}} e^{\frac{\varepsilon_{i}}{\theta_{i}}} e^{-e^{\frac{\varepsilon_{i}}{\theta_{i}}}}$
and
$F_{i}(z)=\int_{\varepsilon_{i}=\infty}^{\varepsilon_{i}=z} f\left(\varepsilon_{i}\right) d \varepsilon_{i}=e^{-e^{\frac{-z}{\theta_{i}}}}$
The error terms are assumed to be independent Extreme Value distributed but allowed to have differing variances. This model requires simulation as well as probit to be solved and the IIA property does not apply here unless all scale parameters are equal to unity. The covariance matrix has zero valued off-diagonal elements and uniquely subscripted diagonal elements:

$$
\left[\begin{array}{ccc}
\sigma_{11}^{2} & 0 & 0 \\
0 & \sigma_{22}^{2} & 0 \\
0 & 0 & \sigma_{33}^{2}
\end{array}\right]
$$

The random utility formulation of equation (1), combined with the assumed probability distribution for the random components in equation (2) and the assumed probability
distribution that an individual will choose alternative $i$ (Pi) from the set C of available alternatives is given by:

$$
\begin{align*}
& P_{i}=\operatorname{Prob}\left(U_{i}>U_{J}\right), \text { for all } j \neq i, j \in C \\
& =\operatorname{Prob}\left(\varepsilon_{j} \leq V_{i}-V_{j}+\varepsilon_{i}\right), \text { for all } j \neq i, j \in C \\
& =\int_{\varepsilon_{i} \rightarrow+\infty}^{\varepsilon_{j} \rightarrow+\infty} \prod_{j \in C, j \neq 1} \Lambda\left[\frac{V_{i}-V_{j}+\varepsilon_{j}}{\theta_{j}}\right] \frac{1}{\theta_{l}} \lambda\left(\frac{\varepsilon_{i}}{\theta_{i}}\right) d \varepsilon_{i} \tag{43}
\end{align*}
$$

where by $\lambda$ (.) and $\Lambda$ (.) we denote the probability density function and cumulative distribution function of the standard type I extreme value distribution respectively and are given by as defined by Johnson and Kotz (in Bhat, 1995; 1970).
$\lambda(t)=e^{-t} e^{-e^{-1}}$
and $\Lambda(t)=e^{-e^{-1}}$
As in the case of MNP, this integral cannot be solved analytically. The IIA property does not apply to this model unless all scale parameters are equal to unity (Munizaga et al., 2000).

The $\log$ likelihood function of HEV model to be maximized can be written as
$\left[\sum_{q=1}^{q=Q} \sum_{i \in C_{q}} y_{q_{i}} \log \left\{\int_{w=-\infty}^{w=+\infty} \prod_{j \in C_{q}, j \neq 1} \Lambda\left[\frac{V_{q i}-V_{q j}+\theta_{i} w}{\theta_{j}}\right] \lambda(w) d(w)\right\}\right.$
Where $C_{q}$ is the choice set of alternatives available to the $q$ th individual and the $y_{q_{i}}$ is defined as follows:
$y_{q_{i}}=\left\{\begin{array}{c}1 \text { if the } q \text { th individual chooses alternative } i \\ q=1,2, \ldots Q, i=1,2, \ldots, I \\ 0 \text { otherwise }\end{array}\right.$
Although travel mode choice has been studied extensively with trip-based as well as individual-based models (Scheiner and Rau 2012), few studies have examined the consequences of network disruptions (Curtis and Perkins 2006). To our knowledge, no previous study has explicitly explored traveler response to subway network disruptions.

### 3.7 Nested Logit Model

The Nested Logit model belong to the family of Generalised Extreme Value Models (GEV). Train (2007) notes that the nested model is appropriate when the choice set facing a decision maker can be partitioned onto subsets, known as nests, in such a way that the following properties hold:

1. For any two alternatives in the same nest, the ratio of probabilities is independent of all other alternatives in the nest. In other words, IIA holds within the nest.
2. For any two alternatives in different nests, the ratio of probabilities can depend on the attributes of other alternatives in the two nests. In other words, IIA does not hold in general for alternatives in different nests.

Let the set of alternatives $\mathfrak{j}$ be partitioned into K nonoverlapping subsets $\mathrm{B} 1, \mathrm{~B} 2, \ldots, \mathrm{Bk}$ and called nests. The utility that individual $n$ obtains from alternative $j$ in nest $B k$ is denoted in the usual manner $U_{i n}=V_{i n}+\varepsilon_{i n}$. The nested logit model is obtained by assuming that the vector of unobserved utility, $\varepsilon_{n=}=\varepsilon_{n 1}, \varepsilon_{n 2}, \ldots, \varepsilon_{n J}$ has the following cumulative distribution: $\exp \left(-\sum_{k=1}^{K}\left(\sum_{j \in B_{k}} e^{-e_{n j} / \lambda_{\kappa}}\right)^{\lambda^{\kappa}}\right)$

For any two alternatives $j$ and $m$ in nest $B_{\kappa}, \varepsilon_{n j}$ is correlated with $\varepsilon_{n m}$. For any two alternatives in different nests the unobserved portion of utility is still uncorrelated: $\operatorname{cov}\left(\varepsilon_{n j}, \varepsilon_{n m}\right)=0$ for any $j \in B_{k}$ and $m \in B_{i}$ with $i \neq \kappa$.

The parameter $\lambda_{k}$ is a measure of the degree of independence in unobserved utility among the alternatives in nest $B_{k}$. A high $\lambda_{k}$ means greater independence and less correlation. A value of,$k=1$ means complete independence in nest $B_{k}$. Obviously, if $x$ $=1$ for all nests, then the GEV distribution simply becomes the produce of independentextreme value terms i.e. the nested logit reduces to the standard logit model.

The probability that individual $n$ chooses alternative $i$ from the choice set is:

$$
\begin{equation*}
P_{n}(i)=P_{n i}=\frac{e^{\frac{V_{n i}}{\lambda_{k}}}\left(\sum_{j \in B_{k}} e^{\frac{V_{n j}}{\lambda_{k}}}\right)^{\lambda_{k-1}}}{\sum_{l=1}^{K}\left(\sum_{j \in B_{i}} e^{\frac{V_{n j}}{\lambda_{i}}}\right)^{\lambda_{i}}} \tag{47}
\end{equation*}
$$

The parameter $\lambda_{k}$ can differ over nests reflecting different correlation among unobserved factors within east nest. However, $\boldsymbol{\lambda}_{\boldsymbol{k}}$ mustbe between 0 and 1 if the model is to ne consistent with utility-maximizing behavior.

An alternative way of presenting the choice probability is by decomposing the observed portion of utility into two parts: (i) a part labeled W that is constant for all alternatives within a nest and (ii0 a part labeled Y that varies over alternatives within a nest. Thus you have: $U_{n j}=W_{n k}+Y_{n j}+\varepsilon_{n j}$, for $j \in B_{k}$, where
$W_{n k}$ depends only on variables that describe nest k .
$Y_{n j}$ depends on variables that describe alternative j .
In this way the nested logit probability can be writer as the product of two standard logit probabilities. Thus the probability of choosing alternative $i \in B_{k}$ is equal to the probability that nest $B_{k}$ is chosen multiplied by the probability that alternative I is chosen given that an alternative in $B_{k}$ is chosen:
$P_{n i}=P_{n B_{k}} \times P_{n i \mid B_{k}}$
Where $P_{n i \mid B_{k}}$ is the conditional probability of chosing I given that an alternative in nest $B_{k}$ is chosen and $P_{n B_{k}}$ is the marginal probability of choosing an alternative in nest $B_{k}$.

These probabilities can be written as $P_{n B_{k}}=\frac{e^{W_{n k}+\lambda_{k} I_{n k}}}{\sum_{i=1}^{K} e^{W_{n k}+\lambda_{i} I_{n i}}}$
$P_{n i \mid B_{k}}=\frac{e^{Y_{n i} / \lambda_{\kappa}}}{\sum_{j \in B_{k}} e^{Y_{n j} / \lambda_{K}}}$
where $I_{n k}=\ln \sum_{j \in B_{k}} e^{Y_{n j} / \lambda_{\kappa}}$, is the inclusive value or inclusive utility for alternative k (nest $B_{k}$ ).

It is important to note that the nested structure does not imply a decision tree or an ordering of how decisions are made. The nesting is purely an empirical method for eliminating IIA violations (Washington et al., 2010).

### 3.8 Summary

The Multinomial Logit model remains the most popular for several convincing reasons (Louviere et al., 2000). Amongst these are:

- It is simple to estimate,
- It has a closed-form specification,
- It delivers fast and reliable models with acceptable tests of model performance,
- Most packaged estimation software is accessible and user friendly,
- The model often has very rich and disaggregate data on attributes of alternatives, which makes it very robust.

The multinomial probit model is an example of discrete-choice model that can test for the possibility that pairs of alternatives in the choice set are correlated to varying degrees. When we relax only the MNL's assumption of equal or constant variance, then we have the heteroskedastic extreme value model or else heteroskedastic logit model.

Empirically, it is not easy to tell which model fits the data best. Nor we can use LRT test or Wald test to distinguish between them. MNL has an advantage over MNP since it is computationally simpler. Even though logit and probit produce different coefficients, predicted probabilities will be similar. In a probit model, $\sigma^{2}=1$, whild in a logit is usually $\sigma^{2}=\frac{\pi^{2}}{3}$. Hence the coefficients of logit and probit are measured on different scales. To compare the coefficients, the probit ones should be multiplied by $\frac{\pi^{2}}{3}=1,81$.

## 4. Study Area

### 4.1 Country/Location of Study

Athens, the capital of Greece, with a population of 3,827,624 citizens (as of 2011 ${ }^{1}$ ) due to a rapid economic growth in late 1990's experienced a large increase in car ownership along with the suburban sprawl. The majority of Athens' citizens live in the suburbs whilst the majority of business is in the city centre. The Athens Urban Public Transport Network is constantly growing. Athens is located in Attica Region (Figure 4-1). Attica Region is one of the 13 Regions of Greece, including the main Grekk port city of Piraieus. The area of the capital region is $427 \mathrm{~km}^{2}$, covering $11.2 \%$ of the total area of the Attica Region.

### 4.2 Public Transport in Athens

As of July 2011, the Athens Mass Transit System consists of:

- OSY S.A. (Greek OEX A.E.)
- A bus network, formerly operated by ETHEL (E $\tau \alpha \varrho \varepsilon i \alpha ~ \Theta \varepsilon \varrho \mu u \varkappa \dot{\omega} \nu$ $\Lambda \varepsilon \omega \varphi \rho \varrho \varepsilon i \omega v /$ Thermal Bus Company). Athens Bus Network consists of 308 Bus lines, with a total length of 6.825 kilometers, with a daily ridership of 1.250.000 passengers and 1700 buses for daily operation.
- An electric trolleybus network, formerly operated by ILPAP (H $\lambda \varepsilon x \tau \varrho о x i \nu \eta \tau \alpha$ $\Lambda \varepsilon \omega \varphi \frac{\varrho \varepsilon i \alpha ~ A \theta \eta v \dot{\omega} v-\Pi \varepsilon!\varrho \alpha \omega \varsigma}{\text { /Electric Buses of Athens-Piraeus). The Athens }}$ Trolley Network consists of 22 lines, with a total length of 379 kilometers, with a daily ridership of 280.000 passengers and 280 trolleys in operation.
- STASY S.A. (Greek: $\Sigma T A \Sigma$ Y A.E.)
- The Athens Tram system, formerly operated by Tram S.A. which was a subsidiary of Attiko Metro S.A.
- The Piraeus-Kifisia urban railway (ISAP), consisting of Athens Metro Line 1.
- The Athens Metro system, the construction of which commenced in 1992 and the first part started operating in 1992. It consists of Metro Line 1 formerly owned by Athens-Piraeus Electric Railways (Line 1), Metro Line 2 and 3, owned by Attiko Metro S.A. and operated by AMEL respectively.

[^5]- A suburban rail system using Hellenic Railways Organisation (OSE) lines, operated by TRAINOSE S.A. under the name Proastiakos. The section between Piraeus, Magoula and Koropi is regarded as the urban part.
- A part of the OSE main line (between Piraeus and Agios Stefanos) operated by Trainose S.A.


### 4.3 Athens Metro

Since our study is dedicated to Metro System Disruptions we will present these systems in more detail. The Athens Metro Network is located within the Athens basin and services the city of Athens and a few of the neighbouring municipalities (Figure 4-1)


Figure 4-1 Athens Metro location within Greece and Attica Region

The Athens Metro as mentioned earlier operates Lines 1, 2 and 3. Lines 2 and 3 serve a total of 855,000 passengers on a daily basis (year $2013^{2}$ ). Nowadays, Lines 2 and 3 of the Athens Metro are 73.3 km long in total (including 20.7 kms of suburban railway line from Doukissis Plakentias station to the Airport) with 36 modern Stations.

[^6]Line 1 (Athens-Piraieus Electric Railways) is 25.6 km long, with 24 stations in operation, and includes 3.1 km of underground line, while the total journey time (in one direction) is 50 minutes (Source: www.stasy.gr) . This line was built in 1869 and electrified in 1904. It reached its full length to Kifissia in 1957 and has undergone various renovations, the major one in view of the Olympics. It has links to both Athens Metro Lines 2 and 3 (in Attiki and Omonoia with Line 2 and in Monastiraki with Line 3). It is also connected with the Suburban Railway at Piraeus, Larissa, and Neratziotissa stations. In addition, Line 1 (Figures 4-2, 4-3) serves more than 415,000 per day ${ }^{3}$. The frequency of trips on weekdays between 5:30 am and 23:30 pm is every 6 minutes in rush hour and 10 minutes in non-rush hours (Source: www.stasy.gr).


Figure 4-2 Athens Metro Line 1 (1930)
source www.stasy.gr

[^7]

Figure 4-3 Athens Metro Line 1-Piraieus Station (2013)
(source www.stasy.gr)

Figure 4-4 present the current Metropolitan railway network (consisting of metro, tram and suburban railway) of Athens along with plans for future extensions.


Figure 4-4 Map of complete Metropolitan railway network according to recent plans for future extensions

Figure 4-5 presents the map of currest status of Athens Fixed Rail Track System (Metro, Tram, Suburban Railway).


Figure 4-5 Athens Fixed Rail Track System Current Status
(Source urbanrail.net)

### 4.4 Service Disruptions in Athens

In this section we present some statistics regarding the frequency of transit strikes or work stoppages on Athens Public Transit. In Figure 4-6 we present the number of days that a transit service was disrupted within 2011.


Figure 4-6 Number of days of 24 hr strikes or work stoppages within $2011^{4}$

[^8]
## Chapter Five

## A Revealed Preference Survey For Metro Disruption

## 5. A Revealed Preference Survey for Metro Disruption

### 5.1 Introduction

Large Metropolitan areas and modern societies highly depend on well-functioning infrastructures especially in the transport sector. Metro systems usually form the backbone of transportation systems, particularly when these systems are integrated with other modes of public transport. When these systems fail to operate, for any reason such as strikes, replacement track works, new signal system, the entire transportation system is affected. Metro systems are vulnerable to both technical (maintenance and reliability) and anthropogenic causes such as personnel strikes, power outages and extreme weather conditions.

However, it is difficult to compare the daily travel pattern with travel decisions over time and during unforeseen situations. In this study, we try to relate passenger's previous experience on mode choice and travel times to their travel decision on transportation alternatives during the partial closure of Metro Line 1.

Metro System operational disruptions are of particular interest to researchers as they can severely hinder transportation patterns in metropolitan areas. Travelers may be forced to alter their travel patterns, miss medical appointments, or even cancel their social activities.

In this chapter we examine the impact of a 5 -month Metro Line closure on the choice of alternative modes during the closure period. Potential changes in choice of mode play themselves out over long time horizons and it is generally unknown whether they will have a permanent character. For example, a long-term closure of a Metro network may lead travelers to explore alternative routes which may be more attractive, force some to relocate or shift to car use. Our study is based on data collected from Metro users on actual mode choices during the closure and a few weeks following system restoration. Questions asked during the closure include: in what ways are commuters affected from a Metro closure? Which mode do they use during the closure? How sensitive are they to increased travel times during the closure period? We address the impacts of the closure on commuters during and after line restoration.

In summary, travel-pattern changes during disruptions in transportation systems have not attracted considerable interest in the literature, despite the practical importance it has for planners and policy makers. Disruptions on Metro systems resulting from

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maintenance upgrade works occur occasionally; however there are no available studies that examine the effects of a long-term disruption on traveler choice of mode during the closure.

### 5.2 Background

In 2009, the Athens Metro Line 1 (Figure 4-1) managing authority (now called STASYex named ISAP) programmed a series of partial closures of the line due to major renovation and upgrade activities during weekend and weekdays). Unfortunately, due to the high complexity of Metro Line 1 renovation tasks (a line being over 100 year old with increased upgrade needs and crossing archaeological sites) and its high daily ridership of over 470,000 passengers1 (which led to the need of at least partial operation of the line in some sections), programming and completion of activities (and therefore closures) was highly uncertain and could not confront to the original schedule of works. As a result, while replacement bus routes were established along disrupted parts in a case-to-case basis, passengers were not adequately informed about their operations. Replacement shuttle bus services were running along the disrupted route serving all intermediate stations. These services were running with a frequency of 10-15 minutes. Furthermore, no fixed headway was kept in operating parts of the line and bus replacement line usage led to a considerable increase in travel times. Transport operators claim that 2009 and 2010 include the most aggressive track and station-work schedule in the Athens Metro history.

During the closure, annual Metro travel cards could be used on all modes of public transportation. In Athens, working is still connected to the traditional office space and only $1 \%$ (European Foundation for the Improvement of Working and Living Conditions, 2009) of the employed population uses new technology and makes different work arrangements.

### 5.2.1 Data Collection

This section describes the results of a travel diary questionnaire survey conducted among Metro Line 1 travelers in Athens effectively after the restoration of the line's operations. The survey was designed to reveal Metro users' behavior as a result of a 5 -month programmed partial closure of Athens Metro Line 1. The survey focused on identifying the criteria that affect travel behavior of Metro users under planned line closures.

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The study proposes an analysis of the mode choice behavior of Metro passengers using RP data. Since actual travel data could not be gathered during the closure, we conducted our survey once the line was opened. Estimation of discrete choice models generally relies on RP data when analyzing travel behavior on existing transport alternatives, systems and facilities (Dissanayake, 2010).

Extensive analysis has been conducted covering aspects as diverse as factors affecting the alternative mode choice, the effect of the partial closure on travel times, the distribution of mode choice across different trip purpose, the relationship between trip duration and alternative mode choice.

Various travel surveys have shed light on the factors that affect mode choice. Travel time uncertainty makes the traveler incur costs in the form of uncertainty of travel time and possible rescheduling costs (Van Loon et al., 2011). Significant factors that have been used in other surveys to describe travel behavior include among others trip's origin and destination, trip purpose, trip duration, access and egress mode and cost.

In the 4 weeks following the line's restoration 1612 travelers were approached on the Metro platforms with a travel questionnaire (Pnevmatikou and Karlaftis, 2011). The questionnaire asked for people's opinion regarding the closure, whether it interrupted their regular travel and, if so, how they solved their transportation problem resulting from the closure. Next, respondents who had indicated that they had been affected by the closure ( $70 \%$ of the data set or 1117 ) were asked to describe how they dealt with the closure.

Respondents were asked to specify the alternative modes they used during the closure. The choice set comprised of the available modes (bus, suburban rail, tram, taxi, car, bicycle, motorcycle, Metro). The survey included questions on origin-destination, any extra costs for parking or taxi fare, door-to-door travel time, time of departure, number of transfers within the journey, egress and access modes to the station and reason for commuting during the closure and a few weeks after the line's restoration.

Additionally, we asked questions regarding the reasons behind the choice of mode during the closure; whether it was due to time restrictions or due to monetary costs, or even because travelers felt that the disrupted network was unreliable in terms of arrival and departure times. Other criteria include safety, lack of information on alternative modes, habit and inertia.

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### 5.2.2 Data Description and Analysis

Figure 5-1 depicts the partial closure of Line 1 (in yellow). The basic characteristics of Metro Line 1 are presented in Chapter 4.

The line closed in November 2009 (the part between Tavros and Faliro), reopened a month later and in January 2010 the part between Kallithea and Faliro was closed and reopened in May 2010 with reduced service and ongoing upgrade work. This is the part of the section connecting the Athens downtown area and the port of Piraeus with stations serving densely populated areas. Note that the municipalities including the affected stations are among the most populated in Attica Region, according to the last census (April 2011). During the closure, travelers had two options: either travel on the partially disrupted Metro line 1(in green) and use alternative modes to travel along the closed route (in yellow), or shift away from Metro Line 1 (yellow/green) to alternative modes for the entire trip.


Figure 5-1 Partial closure of Metro Line 1 between Faliro and Tavros (closed section is in yellow)

During the partial closure of Metro line 1, there was no real time public transit information, and no fixed headways between train arrivals. This lack of information can act as a barrier to individuals traveling on this route. As a result Metro travelers have been experiencing significant delays on their trips as a result of reduced service. In order to minimize the disruptions, the transport operators introduced a number of replacement bus services named X13, X14, X16, X17 running along the disrupted route.

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In all these situations of scheduled or not Metro line closures, passenger demand has been affected as a result of passenger shifting to alternative modes (buses, private cars, taxis). This change in passenger demand is mostly reflected by an increase in car usage and consequently in road traffic.

### 5.2.3 Survey Design

The data required for investigating travel behavior caused by the 5-month closure of the line was collected with the use of questionnaires. We adopted a paper-based survey approach to collect information from Metro travelers for several reasons. The survey was conducted in early June 2010 on the platforms of Metro Line 1 stations. The interviewers had sufficient time between train arrivals to undertake the survey since the frequency of Metro line 1 was around 6 minutes in peak hour and 10 in off-peak hour.

The questionnaire contained a series of RP questions, where respondents stated their mode choice in two different situations:

1. During a partial Metro closure
2. When the line reopened

We label the first trip the 'alternative trip' and the mode of transport on the alternative trip is denoted the 'alternative mode'. We label the second trip the 'current trip' and the mode of transport on the reference trip is denoted the 'current mode' (See figure 5-2).


Figure 5-2 Graphical representation of the definitions used in the analysis of the questionnaire

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Each respondent was asked to report the departure time, the trip time, cost (taxi fare or parking cost, there was no extra cost for public transport), origin and destination of trip, access and egress modes to the Metro stations and purpose of the trip. All of the variables (except for cost) referred to both the alternative and the current trip. Afterwards respondents were asked to report the criteria based on which they chose the alternative mode. They could choose between six (6) criteria such as travel time, travel cost, safety, reliability, lack of information, car availability or report their own different one.

In the RP survey stated above respondents were primarily asked whether the partial closure of the Metro network affected their usual way of travelling. The question was phrased as "Has the partial closure of the network affected your usual way of travelling by Metro?" If the respondent answered they he had not been affected by this disruption, the survey was stopped. The respondents who have been affected by the closure were then asked to report the alternative way of travelling during the disruption and to state whether they have been using the Metro line 1 for part of their trip or they have shifted to alternative ways of travelling. It has been assumed that all modes are deterministically available to the individual. Information on car availability was collected on further question. The sets of choices given to the individuals are as follows:

1. Car (as driver)
2. Car (as passenger)
3. Bus/electric trolley bus
4. Metro Lines 1, 2 and 3
5. Tram
6. Suburban railway
7. Bicycle
8. Pedestrian
9. Motorcycle
10. Taxi

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11. Other

These categories can be broadly categorized into the following 4 groups:

1. Public Transport Group; includes all Fixed Rail Track networks plus trolley/bus
2. Car group; includes car driver and passenger
3. motorcycles, bicycles, pedestrian
4. Taxi Other;

The candidate trip characteristics that have affected the choice set generation process are:

1. Departure time of day
2. Trip purpose
3. Car availability
4. Travel time (door-to-door : including in-vehicle time, waiting time, parking search time, walk time) of alternative trip
5. Travel time (door-to-door: including in-vehicle time, waiting time, parking search time, walk time) of current trip
6. Travel cost

Travel purpose was categorized as follows: (i) work, (ii) education, (iii) fsocialy (iv) other. The data from the completed survey was imported in Microsoft Access and then into SPSS to label and code the variables appropriately. Finally screening and cleaning steps were undertaken to ensure consistency of the records. Records with missing data were deleted or completed if sufficient information existed. A total of 1612 questionnaires were collected, based on the $2 \%$ of the daily passengership of each surveyed station. The final sample included 1593 complete and valid questionnaires.

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### 5.3 Analysis and Results

### 5.3.1 Distribution of Respondents on Modes

The initial interesting result of the survey was the determination of the proportion of Metro passengers affected by the closure. As can been seen from Table 5-1, a 70\% (1117 questionnaires) of Metro's passengership had been affected by the partial closure, while $30 \%$ (476 questionnaires) reported that they were either tourists or non-regular users of the Metro. The latter were thanked and stopped the survey, as they were out of the targeted survey population.

Table 5-1 Mode choice statistics per alternative trip

|  | No of passengers | Percentage |
| :--- | :--- | :--- |
| Affected by closure | 1117 | $70 \%$ |
| Not affected | 476 | $30 \%$ |
| Total | 1593 | $100 \%$ |

From those individuals who reported "affected by the closure", only 643 (58\%) continued using Metro Line 1 for part of their trip despite the long delays. The remaining $474(42 \%)$, who reported that their trip had been altered in some way due to the disruption, shifted to other modes and did not use Metro line 1. We label the former as Group 1 and the latter as Group 2 (Figure 5-3).


Figure 5-3 Travelers' response to the 5month closure

The results of the survey, also, revealed some interesting characteristics of Metro passengers' behavior. It appears that a large percentage of passengers of Group 1 use a combination of modes to get to their destination (Table 5-2) on their alternative trip. All passengers falling in the Group 1 category used a combination of Metro plus one or two other modes to reach their destination during the disruption. Due to limited network coverage only $13 \%$ of passengers who continued to use Metro Line 1 despite its partial closure, used only one mode including the Metro system during the closure period. About half of the Metro passengers (58\%) used the replacement bus service only, for their trip between the disrupted stations. It is obvious that only $7 \%$ of passengers used private modes (car, taxi) to complete their trip.

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Table 5-2 Mode combinations per alternative trip for Group 1

| Type of Mode | Mode combinations | No of respondents | Percentage |
| :--- | :--- | :--- | :--- |
| Metro Passengers | CAR (DR OR PAX) | 23 | $4 \%$ |
|  | BUS (normal service) | 56 | $9 \%$ |
|  | X13 (replacement bus <br> service) | 374 | $58 \%$ |
|  | BUS-X13 | 60 | $9 \%$ |
|  | TAXI | 18 | $3 \%$ |
|  | BUS-TAXI | 12 | $2 \%$ |
|  | WALK | 86 | $13 \%$ |
|  | OTHER | 14 | $100 \%$ |

Results are quite different in Group 2, as shown in table 5-3. For example, about half $(43 \%)$ of the ex-Metro passengers used bus services just for their daily trip during the closures, while $32 \%$ shifted to other (mostly private) modes ( $19 \%$ used cars, $12 \%$ used taxi, $1 \%$ used bikes).

Table 5-3 Mode combinations per alternative trip for Group 2

| Type of Mode | Mode combinations | No of respondents | Percentage |
| :--- | :--- | :--- | :--- |
|  | CAR (DR OR PAX) | 91 | $19 \%$ |
|  | BUS (normal service) | 166 | $35 \%$ |
|  | X13 (replacement bus service) | 22 | $5 \%$ |
| Ex Metro Passengers | BUS-X13 | 13 | $3 \%$ |
|  | TAXI | 59 | $12 \%$ |
|  | METRO | 21 | $4 \%$ |
|  | CAR-METRO | 11 | $2 \%$ |
|  | BUS-TAXI | 11 | $2 \%$ |
|  | BUS-METRO | 52 | $11 \%$ |
|  | WALK | 13 | $300 \%$ |
| All | OTHER | 15 | 474 |

Table 5-4 summarizes the sample distribution on alternative mode groups for groups 1 and 2 respectively. Individuals had in most cases used a combination of modes to get to their final destination but in most cases they only used one group of modes (public transport or taxi or car).

Table 5-4 Mode choice statistics per alternative trip

| Alternative Trip | Public transport <br> group | Car group | Taxi | Taxi |
| :--- | :--- | :--- | :--- | :--- |
| Group 1 | 532 | 23 | 32 | 112 |
| Group 2 | 310 | 110 | 77 | 23 |
|  | 78 |  |  |  |

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Findings indicate that the majority of train users (in both groups 1 and 2) chose the lowest cost mode (public transport) as an alternative mode to Metro Line 1 during the closure. In Group 1 there is a larger tendency to use public transport for the disrupted part of the trip. This finding is expected as public transport for those 5 months and between those disrupted stations was free for all public transport card and ticket holders. No additional fee was charged for an extra transfer on the public transport network due to the closure. During the disruption, the Athens Metro Company had provided an extra bus running free of charge every 5-10 minutes between the disrupted stations. The second highest share of train users in Group 1 decided to either walk (mode group:"Other") or take a bike between the closed stations. Note that the distance between closed stations is 15-20 minutes' walk, so it is easy for someone to walk or cycle. Park and ride or taxi had a low share among train users in Group 1. In Group 2 though, respondents were more willing to shift to their cars in order to get to their destination, compared to Group 1.

Note that the total of each group does not add to the total of responses because most travelers used more than one mode of each group. For Group 1 and specifically for Public Transport group, maximum number of modes used within this group was 3 modes. In simple words, passengers from Group 1 had to transfer maximum two times (eg. change 2 buses or use Metro and bus). Tables 5-5 and 5-6 present the number of total respondents with respect to their access and egress modes during their current trip for Groups 1 and 2 respectively.

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|  | Table 5-5 Mode choice statistics per access mode of current trip |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Current Trip | Public Transport <br> group | Car group | Other | Taxi | Metro Line 1 |
|  | 190 | 24 | 423 | 6 | 643 |
|  | $(30 \%)$ | $(4 \%)$ | $(66 \%)$ | $(1 \%)$ | $(100 \%)$ |
| Group 2 | 180 | 24 | 267 | 3 | 474 |
|  | $(38 \%)$ | $(5 \%)$ | $(56 \%)$ | $(1 \%)$ | $(100 \%)$ |

Table 5-6 Mode choice statistics per egress mode of current trip

| Current Trip | Public Transport group | Car group | Other | Taxi | Metro Line 1 |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Group 1 | 157 | 28 | 452 | 7 | 643 |
|  | $(24 \%)$ | $(4 \%)$ | $(70 \%)$ | $(1 \%)$ | $(100 \%)$ |
| Group 2 | 108 | 20 | 343 | 3 | 474 |
|  | $(23 \%)$ | $(4 \%)$ | $(72 \%)$ | $(1 \%)$ | $(100 \%)$ |

Most of the respondents of both groups walked to the Metro stations of Line. This finding is consistent with a survey conducted on behalf of Athens Metro in 2008 (TRADEMCO - ADO, 2010) which stated that $65 \%$ of travelers who use Metro Line 1 walk to the stations ( $62 \%$ access and $69 \%$ egress mode). The second most popular access and egress mode to the stations is public transport. Car was found to be the least preferable mode ( $4-5 \%$ ). Both tables indicate that Metro travelers are frequent public transport users for the whole length of their trip. This is the case for most Metro stations within the inner city centre as very few Metro stations offer free park \& ride facilities for Metro travelers. Only 4\% of Metro passengers (in Groups 1 and 2) uses car in order to access or egress the Metro stations.

Table 5-7 shows how respondents chose their alternative mode of travel during the network closures.

Table 5-7 Mode choice and criteria

|  | Cost | Time | Car <br> availability | Security | Reliability | No prior <br> information* | Other <br> reasons | Total |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Group 1 | 267 | 271 | 50 | 6 | 43 | 63 | 79 | 643 |
| Group 2 | 96 | 324 | 62 | 3 | 23 | 16 | 65 | 473 |
| *about station closure and service adjustment |  |  |  |  |  |  |  |  |

The figures in Table 5-7 reveal some interesting characteristics of the different groups. First, Group 1 chooses the lowest cost and fastest mode, while in Group 2 there is a larger tendency to choose the fastest mode. Time values more for those who shifted away from Metro during the closure.

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There are sufficient observations in Group 1, that indicate that passengers chose the alternative mode because they were not informed about the closure or they had no information on alternative routes and modes. Many respondents indicated that it was their "only alternative" and they could not specify some other criteria. This answer could be related to the density of the area and the lack of inadequate public transport network of the area or even more to car availability.

Table 5-8 summarizes the mode choice distribution on alternative mode compared to the purpose of the trip.

Table 5-8 Mode choice and purpose of travel

|  | Work | Education | Social | Other | Total <br> Responses |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Group 1 | 369 | 136 | 73 | 65 | 643 |
| Group 2 | 305 | 70 | 47 | 52 | 474 |

It is interesting to compare Group 1 and Group 2 in context of trip purpose. Before we do so we stress that such a comparison has its limitations for the following reasons:

- There is one category of travelers who did not return to using Metro even when the stations reopened. This percentage of train users was not easy to find and contact.
- The survey took place just a few weeks after the line was opened and therefore, there might be a portion of travelers who were not informed about this. This implies that the system might not have reached equilibrium at that point.

The figures in Table 5-8 indicate that there is a larger share in Group 2 of commuters ( $64.3 \%$ ) compared to commuters in Group 1 ( $57.4 \%$ ) who chose to shift to alternative modes other than Metro line 1 which was disrupted at the time. These findings support that commuters are inflexible with time and prefer shifting to alternative modes to avoid delays and use more reliable modes. In addition, there is a lower share of students in Group 2 ( $14.8 \%$ ) compared with Group $1(21.1 \%)$. This finding could indicate the fact that students are more flexible in travel time and less flexible in travel cost.

### 5.3.2 Travel Time and Mode Choice

It is interesting to compare travel time between the alternative trip and the current trip (Table 5-9).

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## Table 5-9 Travel Time-Group 1

| Scenario | Total <br> Responses | Mean travel <br> time <br> (minutes) | MIN | MAX | STDV | $\boldsymbol{\sigma} / \mathbf{0 , 1} \boldsymbol{\mu}$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :---: |
| During Closure- <br> Alternative Trip | 643 | 63.57 | 15 | 150 | 26.36 | 4,14 |
| Today travel- <br> Current Trip | 643 | 45.90 | 5 | 120 | 21.69 | 4,73 |

Average travel time for passengers during closures was approximately 64 minutes, while after stations were opened average travel time was calculated 19 minutes less ( $\sim 46$ minutes).

In order to get better understandings of travel time saving or loss due to the mode shift during the 5 -month closure, travel time is split into three time groups so as to describe short, medium-size and long trips. Therefore, trips that last up to 45 minutes are categorized as short trips, trips between 45 and 75 minutes are considered as mediumsize trips and trips longer than 75 minutes are considered as long trips.

Tables 5-10, 5-11 and 5-12 present the saving or loss in travel time due to the disruption by the Metro line closure for each time group and for Metro travelers that fall in Group 1.

We define as travel time difference (TTD) the difference in travel time of alternative trip minus the travel time of current trip. When TTD is positive, it means that passengers traveled longer than usual during the closure (time loss). When TTD is negative, it means that passengers saved time given the mode choice they made for the alternative trip.

Travel Time difference (TTD)= Travel time of "alternative trip"-Travel time of "current trip"

When TTD $>0$ is time loss
When TTD $<0$ is time saving
When TTD=0 no time saving

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Table 5-10 Group 1-TTD for short alternative trips

| TTD | Percentage |
| :--- | :--- |
| No time saving | $12 \%$ |
| 5 | $12 \%$ |
| 10 | $34 \%$ |
| 15 | $19 \%$ |
| 20 | $8 \%$ |
| 25 | $6 \%$ |
| 30 | $2 \%$ |
| 35 | $3 \%$ |
| Negative | $4 \%$ |

As shown in Table 5-10, 80\% of Metro passengers who on current trip reported that they travelled short daily trips ( $0-45$ minutes), shifted to alternative modes and traveled up to 25 minutes more during the closure. Only $4 \%$ of travelers saved time during closures by shifting to other transportation alternatives.

Table 5-11 Group1-TTD for medium-size alternative trips

| TTD | Percentage |
| :---: | :---: |
| No time saving | $13 \%$ |
| 5 | $3 \%$ |
| 10 | $15 \%$ |
| 15 | $24 \%$ |
| 20 | $19 \%$ |
| 25 | $5 \%$ |
| 30 | $10 \%$ |
| 35 | $2 \%$ |
| 40 | $2 \%$ |
| $>40$ | $4 \%$ |
| Negative | $2 \%$ |

Regarding medium-size trips, $80 \%$ of Metro passengers who on current trip reported that they travelled longer daily trips (45-75minutes), shifted to alternative modes and traveled up to an additional 35 minutes during the closure. Half of them travelled 15-20 minutes longer than usual.

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Table 5-12 Group 1-TTD for long alternative trip

| T'TD | Percentage |
| :--- | :--- |
| No time saving | $8 \%$ |
| 5 | $1 \%$ |
| 10 | $6 \%$ |
| 15 | $6 \%$ |
| 20 | $22 \%$ |
| 25 | $4 \%$ |
| 30 | $29 \%$ |
| 35 | $1 \%$ |
| 40 | $6 \%$ |
| $>40$ | $17 \%$ |
| Negative | $0 \%$ |

Table 5-12 shows that passengers traveling long distances faced the biggest disruption during the closure and this is approximately up to 40 minutes for the $80 \%$ of the passengers. A third of the travelers who fall in this category travelled longer by half an hour.

Table 5-13, 5-14 and 5-15 present the saving or loss in travel time due to the disruption by the Metro line closure for each time group and for Metro travelers that fall in Group 2.

Table 5-13 Group 2-TTD for short alternative trips

| TTD | Percentage |
| :---: | :---: |
| No time saving | $13 \%$ |
| 5 | $10 \%$ |
| 10 | $11 \%$ |
| 15 | $4 \%$ |
| 20 | $4 \%$ |
| 25 | $2 \%$ |
| Negative | $56 \%$ |

Metro passengers who shifted to alternative modes and did not use Metro Line 1 during the closure travelled quicker to their destinations during the closure as shown in Table 514. Only a $30 \%$ of Group 2 passengers faced delays during their alternative routes. More than half of them travelled faster to their destinations during closure. This is partly because they used mainly private means and therefore avoided transfers and partly because they shifted to taxis.

Table 5-14 Group 2-TTD for medium-size alternative trips

| TTD | Percentage |
| :--- | :--- |
| No time saving | $13 \%$ |
| 5 | $3 \%$ |
| 10 | $15 \%$ |
| 15 | $15 \%$ |
| 20 | $14 \%$ |
| 25 | $3 \%$ |
| 30 | $11 \%$ |
| $>30$ | $9 \%$ |
| Negative | $17 \%$ |

Table 5-14 indicates that more than $75 \%$ of the passengers who traveled either by car or public transportation during closure for more than 45 and less than 75 seem to have experienced significant delays of up to 30 minutes.

| Table 5-15 Group 2-TTD for long alternative trips |  |
| :--- | :--- |
| TTD | Percentage |
| No time saving | $11 \%$ |
| 5 | $1 \%$ |
| 10 | $3 \%$ |
| 15 | $7 \%$ |
| 20 | $10 \%$ |
| 25 | $27 \%$ |
| 30 | $4 \%$ |
| $>30$ | $35 \%$ |
| Negative | $6 \%$ |

Finally, the longer a trip was the less saving it had with respect to the alternative chosen route (Table 5-15). Only a $6 \%$ of this category of passengers travelled faster to their destination during their alternative trip compared to their current trip.

### 5.4 Theoretical Framework

The theoretical basis for modeling the choice of mode during the closure period is random utility theory. Each traveler chooses whether to use the disrupted part of Metro Line 1 during the 5month closure that determine utility maximization based on the attributes of interest. Heterogeneity among travelers leads to variation in choices. Variation in choices leads to variation in attribute levels.

The overall utility the traveler n derives from choosing mode $i, U_{\text {in }}$ consists of a deterministic component $V_{i n}$ and a random component $\varepsilon_{i n}$. The deterministic

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component is modeled as an indirect utility function conditional on the vector of choice of mode attributes and the vector of traveler and trip characteristics which are specific to individual traveler and influence utility. Denote $P_{n}(i)$ as the probability that the traveler n chooses mode $i$ (in our case travel on the disrupted part of the Metro Line 1) rather than mode $j$ (choose alternative way of travel during the 5month closure) among all the feasible alternative modes available in the set $C_{n}$. If the random components are identically and independently distributed (IID), Type I Extreme Value, then $P_{n}(i)$ is of the logit form:
$P_{\text {in }}=\operatorname{Prob}\left(V_{i n}+e_{i n} \geq V_{j n}+e_{j n}: \mathrm{j} \in C_{n}\right)=\exp \left(V_{i n}\right) / \Sigma j \in C_{n} \exp \left(V_{j n}\right)$.
Since metro users surveyed are presented with two base choices (either continue traveling on the disrupted line and for the disrupted part used other modes, either shifted to other modes), the structure of the set of choices $C_{n}$ restricts to two.

The demand model describing the revealed preference data assumes that individual traveler $i$ allocated its income between a composite commodity and a recreation commodity. This allocation depends on the travel cost of each trip and other factors denoted $x_{i}$.

We developed a model to focus on the choice of mode during the closure period. Table 5-16 presents traveler characteristics.

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Table 5-16 Sample characteristics

| Characteristics | Type | Statistics | \% | Description |
| :---: | :---: | :---: | :---: | :---: |
| Number of cases |  | 1593 |  |  |
| Impact on commuters |  |  |  |  |
| YES | Dummy | $\mathrm{F}(1)=1117$ | 70\% | $=1$ if closure affected travelers |
| NO |  | $\mathrm{F}(0)=476$ | 30\% | $=0$ if not |
| Use of disrupted Metro Line 1 during closure as primary commute mode |  |  |  |  |
| YES | Dummy | $F(1)=643$ | 58\% | $=1$ if traveler remained on the disrupted Metro during closure |
| NO | Dummy | $F(0)=474$ | 42\% | $=0$ if shifted to alternative modes during closure |
| Travelers using car (not as primary mode) after the line's restoration | Dummy | $F(1)=92$ | 8\% | $=1$ if travelers used car |
|  |  | $F(0)=1025$ | 92\% | $=0$ if otherwise |
| Travelers who used car during closure | Dummy | $\mathrm{F}(1)=138$ | 12\% | $=1$ if travelers used car |
|  |  | $\mathrm{F}(0)=979$ | 88\% | $=0$ if otherwise |
| Travelers who used replacement bus services during closure | Dummy | $\mathrm{F}(1)=485$ | 43\% | $=1$ if travelers used replacement bus service |
|  |  | $F(0)=632$ | 57\% | $=0$ if otherwise |
| Average travel time during closure |  | 57.48 |  |  |
| Travel_Time_0-20 min | Dummy | $F(1)=106$ | 9\% | $\begin{aligned} & =1 \text { if travel time during closure is }>0 \text { and } \\ & <20 \text { mins } \\ & =0 \text { otherwise } \end{aligned}$ |
|  |  | $F(0)=1011$ | 81\% |  |
| Travel_Time_21-40 min | Dummy | $F(1)=257$ | 23\% | $=1$ if travel time during closure is 21 and $<40$ mins |
|  |  | $F(0)=860$ | 77\% | $=0$ otherwise |
| Travel_Time_41-60 min | Dummy | $F(1)=410$ | 37\% | $=1$ if travel time during closure is $<41$ and $>60 \mathrm{mins}$ |
|  |  | $F(0)=707$ | 63\% | $=0$ otherwise |
| Travel_Time_60+ min | Dummy | $F(1)=344$ | 31\% | $=1$ if travel time during closure is $>60$ mins |
|  |  | $F(0)=773$ | 69\% | $=0$ otherwise |
| Average travel time after line's restoration |  | 45.29 |  |  |
| Travel_Time_0-20 min | Dummy | $F(1)=178$ | 16\% | $=1$ if travel time during closure is $>20 \mathrm{mins}$ |
|  |  | $\mathrm{F}(0)=939$ | 84\% | $=0$ otherwise |
| Travel_Time_21-40 min | Dummy | $F(1)=395$ | 35\% | $=1$ if travel time is $>21$ and $<40$ mins |
|  |  | $\mathrm{F}(0)=722$ | 65\% | $=0$ otherwise |
| Travel_Time_41-60 min | Dummy | $F(1)=366$ | 33\% | $=1$ if travel time $>41$ and $<60 \mathrm{mins}$ |
|  |  | $\mathrm{F}(0)=751$ | 67\% | $=0$ otherwise |
| Travel_Time_61+ min | Dummy | $F(1)=178$ | 16\% | $=1$ if travel time $>60 \mathrm{mins}$ |
|  |  | $\mathrm{F}(0)=939$ | 84\% | $=0$ otherwise |
| Number of transfers during closure ( n modes-1) |  |  |  |  |
| Transfer_0 | Dummy | $\begin{aligned} & \mathrm{F}(1)=451 \\ & \mathrm{~F}(0)=666 \end{aligned}$ | $\begin{aligned} & \hline 40 \% \\ & 60 \% \end{aligned}$ | $\begin{aligned} & =1 \text { in case of no transfers } \\ & =0 \text { if otherwise } \end{aligned}$ |
|  |  |  |  |  |
| Transfer_1 | Dummy | $F(1)=392$ | 35\% | $=1$ in case of 1 transfer |

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|  |  | $F(0)=725$ | 65\% | $=0$ if otherwise |
| :---: | :---: | :---: | :---: | :---: |
| Transfer_2 | Dummy | $F(1)=220$ | 19\% | $=1$ in case of 2 transfers |
|  |  | $F(0)=897$ | 81\% | $=0$ if otherwise |
| Transfer_3+ | Dummy | $F(1)=54$ | 1\% | $=1$ in case of 3 or more transfers |
|  |  | $\mathrm{F}(0)=1063$ | 99\% | $=0$ if otherwise |
| Number of transfers after line's |  |  |  |  |
| Transfer_0 | Dummy | $\mathrm{F}(1)=312$ | 28\% | $=1$ in case of no transfers |
|  |  | $\mathrm{F}(0)=805$ | $72 \%$ | $=0$ if otherwise |
| Transfer_1 | Dummy | $\mathrm{F}(1)=527$ | 47\% | $=1$ in case of 1 transfer |
|  |  | $\mathrm{F}(0)=590$ | 63\% | $=0$ if otherwise |
| Transfer_2 | Dummy | $F(1)=268$ | 24\% | $=1$ in case of 2 transfers |
|  |  | $\mathrm{F}(0)=849$ | 76\% | $=0$ if otherwise |
| Transfer_3 | Dummy | $F(1)=10$ | 1\% | $=1$ in case of 3 transfers |
|  |  | $\mathrm{F}(0)=1107$ | 99\% | $=0$ if otherwise |
| Work | Dummy | $F(1)=674$ | 60\% | $=1$ if travel purpose is work |
|  |  | $F(0)=443$ | 40\% | $=0$ if otherwise |
| Education | Dummy | $F(1)=206$ | 18\% | $=1$ if travel purpose is education |
|  |  | $\mathrm{F}(0)=911$ | 82\% | $=0$ if otherwise |
| Social | Dummy | $F(1)=120$ | 11\% | $=1$ if travel purpose is social |
|  |  | $\mathrm{F}(0)=997$ | 89\% | $=0$ if otherwise |
| Other | Dummy | $F(1)=117$ | 11\% | $=1$ if travel purpose is other |
|  |  | $\mathrm{F}(0)=1000$ | 89\% | $=0$ if otherwise |

The most important explanatory variables included travel time post-disruption, departure time, main trip purpose, transfer inconvenience (measured as number of transfers within a journey), and use of car (as egress or access mode to the Metro stations) postdisruption.

More than half ( $58 \%$ ) of those affected continued using the disrupted network despite the significant delays, while the remaining ( $42 \%$ ) shifted to alternative modes other than Metro (Table 5-16). Results showed that travel times during the closure changed moderately compared to travel times post closure for the travelers who remained on the disrupted network and used the operating part of Metro Line 1. Average travel time for these passengers during closures was approximately 61 minutes (standard deviation= 26.39), while after stations were opened average travel time was calculated 12 minutes less ( $\sim 49$ minutes and standard deviation= 25.44). On the other hand, travelers who shifted away from Metro Line 1 and did not use the disrupted part of Metro Line 1 during the closure, experienced much shorter travel times with an average of 49

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(standard deviation=25.5) minutes during the closure compared to 45 minutes (standard deviation=21.6) reported post closure (an average 4 minute delay).

Interestingly, 754 out of 1117 (about 68\%), travelled longer than 40 minutes during the closure period, while post-disruption only 544 out of 1117 (about 48\%) travelled longer than 40 minutes. A significant share of travelers ( $42 \%$ ) changed their daily commuting route because of increased travel times. Surprisingly, post-disruption the number of travelers who reported making 2 transfers during their journey increased. This may have happened because during closure travelers adopted alternative longer routes probably at a greater cost, including fewer transfers. We excluded travelers who reported not being permanent residents of Athens, and were out of the disrupted region for the entire period of the closure.

### 5.5 Impacts on Commuters

In the survey we asked two general questions: a) journey travel time during the closure period and, b) journey travel time once the line was restored. Questions regarding travel cost were not included in the survey as it would have been difficult for the travelers to recall and calculate in such short time (note that the collection of the questionnaires took place on the platforms while waiting for the metro), especially for the those who used either a combination of modes during the closure or used private modes. Another reason was that travelers with weekly/monthly/yearly travel cards were offered free rides on the the buses and the tram network for the entire period of the disruption.

Comparing post disruption travel time to travel times during the closure (Table 5-17), we found that travel conditions (in terms of travel time) were worse for $50 \%$ of travelers during the closure. Similar percentage ( $40 \%$ ) reported encountering delays of up to 10 minutes. Only $10 \%$ of travelers reported that travel conditions were better than usual. It appears that alternative modes/routes adopted by some commuters actually improved travel times possibly of course at higher costs.

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Table 5-17 Travel conditions during closure

|  | $\mathbf{N}$ | $\%$ |
| :--- | :--- | :--- |
| Much worse in relation to usual travel time (Number reporting delays $>10 \mathrm{~min})$ | 561 | $50 \%$ |
| About the same $(0<\Delta \mathrm{t}<10$ minutes) | 451 | $40 \%$ |
| Much better (Number reporting arriving faster than normal; $\Delta \mathrm{t}<0)$ | 105 | $10 \%$ |
|  | Total | $100 \%$ |

As earlier discussed, a large proportion of travelers shifted away from Metro Line 1 during the closure to avoid excessive delays. Travelers were asked whether during the closure they used a different mode of travel than they normally would. Travelers who did not remain on Metro Line 1 were then asked which mode(s) they used. The objective of this study is to know the overall shares of people who changed their use of mode. Table 5-18 presents the modes used during the closure and the change in shares during the closure. Table 5-18 indicates that, during closure, $5 \%$ of respondents increased car use (either as driver or passenger), $8 \%$ increased taxi use, $43 \%$ used the replacement bus services which run along the disrupted route, and $1 \%$ increased their use of the suburban rail line.

Table 5-18 Mode shares during closure and after restoration

|  | Drive | Taxi | Use replacement <br> bus service | Bike/ <br> Motorcycle/ <br> Other | Tram | Bus <br> lines | Metro |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| During closure | $13 \%$ | $10 \%$ | $43 \%$ | $1 \%$ | $2 \%$ | $32 \%$ | $12 \%$ |
| Following line's <br> restoration | $8 \%$ | $<2 \%$ | $\mathrm{n} / \mathrm{a}$ | $2 \%$ | $<2 \%$ | $47 \%$ | $38 \%$ |
| Change in shares | $+5 \%$ | $+8 \%$ | $+43 \%$ | $-1 \%$ | $+1 \%$ | $-15 \%$ | $-26 \%$ |

Table 5-19 presents traveler criteria regarding mode choice. Interestingly, time constraints were reported to be the primary criterion for travelers followed by cost constraints. Most travelers reported both time and cost. Interestingly, many travelers reported that habit and inertia were the main reasons for remaining on the disrupted network.

Table 5-19 Criteria for Mode choice during the closure

| Criterion | Cost | Time | Car <br> availability | security | Reliability | No prior <br> information* | Habit |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| No of <br> respondents | 363 | 595 | 112 | 9 | 66 | 79 | 144 |
| $*$ |  |  |  |  |  |  |  |

[^10]
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### 5.6 Alternative Travel Pattern Model

Choice models are widely used in transportation, economic and marketing fields to model the choice of one among a set of mutually exclusive alternatives. This study aimed to model the use of the operating part of Metro Line 1 during the closure using the Binary Logit model (Washington et al, 2010). When travelers are faced with two dominant alternatives, the situation is termed as a binary choice set. Model estimation was done using the NLOGIT software package (v5.0).

The dependent variable in the model developed is the 'use of the partially disrupted metro network during the 5 -month closure of Athens Metro Line 1. A value of zero was given to those travelers who did not use the partially disrupted metro network during the 5 -month closure while the value of 1 was given to those who used it.

Consequently, the probability $\mathbf{P}_{\text {in }}$ that the traveler $n$ chooses mode i (in our case travel on the disrupted part of the Metro Line 1) rather than mode $j$ (choose alternative way of travel during the 5month closure) among all the feasible alternative modes available in the set $\mathbf{C}_{\mathbf{n}}$. If the random components are identically and independently distributed (IID), Type I Extreme Value, then $\mathbf{P}_{\mathbf{i n}}$ is of the logit form:
$P_{\text {in }}=\operatorname{Prob}\left(V_{i n}+e_{i n} \geq V_{j n}+e_{j n}: \mathrm{j} \in C_{n}\right)=\exp \left(V_{i n}\right) / \Sigma \mathrm{j} \in C_{n} \exp \left(V_{j n}\right)$

The model application is based on the utility theory, which assumes that the decisionmaker's preference for an alternative is captured by a value called utility. The overall utility the traveler $n$ derives from choosing mode $i, U_{i n,}$ consists of a deterministic component $V_{i n}$ and a random component $\varepsilon_{i n}$ which measures all the unobserved attributes related to the utility. The deterministic component is modeled as an indirect utility function conditional on the vector of choice of mode attributes and the vector of trip characteristics which are specific to individual traveler. The utility of traveler $n$ when choosing alternative $i$ is defined as:
$U_{i n}=V_{i n}+\varepsilon_{i n}$
Where

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$\boldsymbol{V}_{\text {in }}=\boldsymbol{a s c} \boldsymbol{c}_{\boldsymbol{i}}+\boldsymbol{\beta}_{i} \boldsymbol{x}_{\text {in }} \quad$ and,
$\boldsymbol{\beta}_{\boldsymbol{i}}$ is the coefficient associated with the alternative
$\boldsymbol{x}_{\boldsymbol{i} \boldsymbol{n}}$ is the variables value
$\boldsymbol{a s c} \boldsymbol{c}_{\boldsymbol{i}}$ is the constant estimated by the model

Since metro users surveyed are presented with two base choices (either continue traveling on the disrupted line and for the disrupted part used other modes, either shifted to other modes), the structure of the set of choices $\boldsymbol{C}_{\boldsymbol{n}}$ restricts to two. The parameters $\beta$ are estimated using the econometric software NLOGIT package (v5.0).

We develop a binary choice model for the choice of alternative travel patterns during a 5month closure of Athens Metro Line 1. The trips of each respondent are defined by the origin and destination pairs that are differentiated for each respondent and are differentiated for their choice to use or not the operating part of the partially closed Metro Line 1. The choice situation $i$ is defined for each respondent $n$ with a choice set of two alternatives in the market segment represented by $I_{c}$. The index in in choice set $I_{c}$ carries the information of whether the traveler used or not the operating part of partially disrupted network.

### 5.7 Analysis of Results

Using the data collected we developed a model to forecast the use of the disrupted Metro Line 1 during the 5 -month closure. The explanatory variables collected from the survey which were included in the model are: travel time post-disruption, education as journey purpose, transfer inconvenience (measured as number of transfers within a journey), and use of car (as egress or access mode to the metro stations) post-disruption. Inclusion of other parameters did not provide any significant improvement in the likelihood ratio test. Table 5-20 presents the estimated parameters.

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Table 5-20 Binary Logit Model: estimation results for travelers who reported affected by the 5month Metro closure


Factors that prove most influential in predicting the use of the operating part of the disrupted Metro Line 1 include influence of usual travel time (before or post closure), number of transfers within a single journey during the closure and trip purpose. We assumed that travelers who use car as part of their journey before or after closure might be more prone to use it during the closure. 'Travelling for education purposes' is found significant at the $90 \%$ confidence level. Among the variables tested, all had significant contribution to the model. Socio-economic variables were not collected as part of this study due to time constraints and mainly because travellers were particularly disappointed by the experienced delays and further questions on their economic and employment status were excluded from the study. One other reason was the limited available time for the survey and the fact that it was face-to-face and would probably not provide the researchers with real data as travellers tend to overestimate these answers.

Some interesting results emerge from the estimated model. We note that the model provided the expected signs for all independent variables. We assume that travel time post disruption is approximately the same with travel time before closure and hence travellers might decide on whether to use the disrupted Metro or not during a closure based on their past experience of travel before the Metro closure.

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For journey travel time, all the parameters have large negative values, indicating that for short journeys (base alternative of 0-20 minutes), travelers remained on the operating part of Metro Line 1. Travel time post disruption was found to have a notable impact with longer journeys more likely to be shifted to alternative modes other than Metro Line 1. For example, travelers who normally travel 60 minutes or more have a higher disutility (coefficient of -1.086) for remaining on the disrupted network compared to travelers who normally travel between 20 and 60 minutes.

The coefficient of 'transfer' is highly significant and positive indicating that the utility of remaining on the disrupted Line increases with the number of transfers. Interestingly, travelers who make 2 or more transfers during the closure are more likely to remain on the metro network compared to those who make 1 transfer.

Students and travelers who made more than 1 transfer during the closure, have an increased flexibility with travel time. Interestingly, students have a higher probability of using Metro Line 1 during the disruption, probably due to cost constraints and time flexibility and unavailability of alternative modes to travel.

Overall, the increase in travel time yields a decrease in the overall utility to travel on the disrupted Metro Line during closures. By contrast, the increase in the number of transfers during the closure yields an increase in the overall utility to travel on the disrupted Metro Line during closures. The marginal effects of each variable on each behavioral response are presented in Table 5-21.

Table 5-21 Binary Logit Model: marginal effects on choice probabilities


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Table 5-21 indicates that travelers who make 1 and 2 transfers are more likely to remain on the disrupted Metro network during the closure. The same is true for students. Travelers who make longer trips ( $>60$ mins) are much less likely to remain on the disrupted network during the closure period and more likely to shift to alternative modes. Interestingly, choice of using the operating part of the disrupted network during closure is not sensitive to usual travel time before or after the disruption (elasticities of -0.114,-$0.161,-0.261$ ). Hence, the value of time for travelers who make 1 and 2 transfers, for students and for travelers who travel longer than 60 mins is low and this suggests that their disposal income is low and therefore it would have been interesting to collect travel cost data, which was difficult at the time of the study.

Based on this finding, we tried to calculate and analyse the impact of travel costs on choice of mode during disruptions in Chapetr 7. Assumptions included using current market costs for fuel price per traveled kilometer, average car speed in Athens Central Business District, transit fare for bus/metro/tram, taxi costs etc.

### 5.8 Conclusions

Commuters confronted with disruptions to Metro networks (e.g. new signal system, replacement track works) experience disturbances that prompt them to select suboptimal routes or modes to avoid disruptions. Studying Metro travel patterns in relation to facility disruption provides a basis for prioritizing future Metro station closures for station improvements and understanding the impacts of such disruptions. Understanding travel patterns of Metro commuters brings together perspectives on the demand side of mobility management.

A revealed preference survey regarding the mode choice of travelers during a 5-month closure was carried out in Athens in 2010. This unique data set contains during-closure and post-closure information from the same respondents which makes it possible to compare what people usually do under normal circumstances and what they actually did during the closure. Overall, based on the binary logistic regression model provided in this paper, we conclude that of the trip characteristic attributes, the number of transfers included within a single journey have the greatest impact on the decision to use or not the disrupted metro network during the closure period. Only trips for educational

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purposes are found to influence the choice of using the operating part of Metro Line 1 during closure.

The observed increase in travel times provides an indicator for the evaluation of the role of public transport in mitigating highway congestion during metro disruptions. Compared to the effects of a transit strike it seems like in longer closure periods the automobile is not always the primary alternative mode as found in transit strike related studies (Coindet, 1998, Zhu and Levinson, 2010;2011).

Our analysis showed that the choice to remain on the disrupted network during the closure was more likely for trips that were made for educational purposes due to schedule flexibility and cost constraints (students usually hold discounted public transport passes and are captive public transport riders). Interestingly, the choice of remaining on the disrupted network is sensitive to previous travel time experience and transfer inconvenience during the closure.

There is some evidence here that unanticipated delays during closures differentially affect traveler choice of mode involving activities done by students. In this case, students are more likely to move activities to another time on the same day and accept increased travel times on the metro network instead of shifting to alternative modes during closure times. The fact that delays may have a greater impact on some people than on others reflects a social dimension to transport planning. However, this study has not revealed the differential impact of metro closures for different socioeconomic groups; hence a complete analysis requires further data collection and study of these elements. Finally, another potential future research direction is to incorporate the empirical findings of this study, with data collected using technologies such as GPS and Bluetooth devices to collect representative data.

This paper is intended to provide a reasonable starting point for travel demand modeling in specific situations of subway closures. Models similar to the ones developed here can prove valuable when planning the delivery of subway upgrades and alternative transport options when lines are closed. Municipalities and transit authorities should learn from past experience and provide options (teleworking, carpooling, free or discounted transit passes, etc) and have contingency plans to make traffic smoother for commuters, based on results presented.

## 6. A Stated Preference Survey for Metro Disruption

### 6.1 Introduction

In this chapter, we provide a detailed description of the case study of the Athens Metro disruption. After giving a brief introduction and reviewing similar work on Metro disruptions we describe in detail our study objectives, the survey design, the pilot study, the interviewing method, the main survey, the mode-choice experiment, we give a detailed description of attributes, the RP data collected, we analyze the sample, the screening process, etc.

Subway network closures caused by events such as unforeseen technical breakdowns, strikes, or planned infrastructure upgrades are not frequent, but when they occur they disrupt public transport operations significantly. These disruptions may be either unexpected, resulting from emergencies or incidents or expected, resulting from maintenance activities and personnel strikes (Pnevmatikou and Karlaftis 2011). Commuters disrupted by significant improvements of the subway network (e.g. new signal system, replacement track works) experience disturbances that force them to alter routes or modes, to avoid disruptions. Transit strikes may reroute traffic, resulting in missed medical appointments, lost jobs, or curtailing of social activities (Urban Transportation Showcase Program 2012). These situations are of particular interest to transport operators as they need to plan ahead for such contingencies to avoid patronage loss in the long-term. Following a major disruption, it is generally difficult to determine how long it takes for network operations to fully recover; travelers may either adjust their travel decisions or experience significant delays. Darmamin et al. (2010) argues that it is difficult to calculate the number of buses that need to be deployed for stranded commuters during a disruption, since the capacity of a bus is very limited compared to a single train. As a result, even if several buses are deployed during a closure, the uncertainty of response times may cause discomfort and inconvenience to many commuters (Darmamin et al., 2010).

Since 2008 in the city centre of Athens (the capital of Greece), a large number of strikes, protests, engineering works have interrupted the normal operation of the Metro network and the usual route and mode of many travelers, which substantially disturbed regular traffic flow patterns on the network. Strikes are a quintessential part of life in Greece and other Mediterranean countries, such as Spain and Italy. Some strikes are in protest, some
in support. They can last a few hours, a few days or a few weeks. The frequency of strikes increased when the government ordered stricter implementation of laws and drastic reforms that impact jobs, salaries and quality and cost of living. But the phenomenon of strikes is not new and will continue beyond austerity and bailouts.

### 6.2 Study objectives

It is unknown how long it takes every time for the network to re-equilibrate immediately after a closure. Travelers either adjust their travel decisions or experience significant delays. According to Goodwin (1992), 'the traveler does not carefully and deliberately calculate a new route each morning whether to go to work by car or by bus. Such deliberation is likely to occur only occasionally, probably in response to some large change in the situation'. Studying subway commuter response regarding facility disruption provides a basis for prioritizing future subway station closures and for understanding the impacts of such disruptions. Since network disruptions are not frequent, behavioral changes cannot be easily monitored since the time available for data collection and analysis is limited. In this context, we investigate alternative mode choices of Subway users for the period following a disruption based on a SP survey recording potential experiences with such events ${ }^{1}$. We use information on previous traveler experience regarding network closures in combination with responses to a programmed subway closure where individuals are presented with a large set of options regarding mode used, travel time, travel cost, and number of transfers. The data used in the current analysis is drawn from a web-based survey of Athens, Greece public transport users.

The primary data related to socio-economic and demographic data of individuals, trip and traveler characteristics and the characteristics of the population based on car ownership status. This information was collected to develop two groups of travelers defined by car ownership status.

Two SP surveys were developed, one for car owners and one for car non-owners. Both addressed commuter choice of mode when faced with a 24 hr personnel Metro strike, higher fuel prices, changes in taxi fares and new forms of public transport such as bus

[^11]priority system which is characterized by shorter travel times and shorter waiting time for bus to arrive. By the time the full study was ready, a number of pre-pilot tests had already been completed on a small number of respondents in order to resolve some issues of concern before releasing the main survey.

Key research questions for this study include: what role does age, income, and frequency of mode use play in how travelers respond to network closures? Will travelers who are more flexible in terms of time consider shifting to private cars more easily or vice versa? Findings may prove useful in understanding changes in Public Transport (PT) user choices and patterns during service disruptions, and in better planning the 'return' of users to PT following closures.

In this study we focus on the analysis of the SP experiment with respect to socioeconomic characteristics of the travelers and questions regarding usual mode of travel, usual travel time to work and flexibility of working hours, because we target on all captive Metro travelers, even those who did not remain on the subway network during the closure.

### 6.3 Preparatory Phase and Pilot Study

A pilot study was distributed a few weeks before the final survey was released. The primary objective of the pilot study was to test the contents of the survey process. The outcome of the pilot study will enable the testing of the following:

1. That the questions are readable
2. The interview length is acceptable and will not cause fatigue
3. Interviewers understanding of the study and how it is to be administered
4. Correct skip or logic of the questions

The main findings of the study are as follows:

- Travelers prefer their set of choices to include maximum 3 choices. They get confused with more alternatives.
- They also prefer travel time to be split in two categories: in-vehicle and out-ofvehicle time (and not wait time, walk time, parking search time, etc) as they give
more importance in the total travel time to their destination during a Metro closure. The same finding applies for cost attribute.
- Comfort and cycling facilities only appeal to a small share of travelers.
- Working schedule and flexibility was considered very important aspect
- On average respondents were able to complete the entire questionnaire in 10 minutes.


### 6.4 Survey Design and Data Collection

### 6.4.1 Data collection

We adopted a web-based survey approach to collect information from public transport users as this type of survey method is relatively inexpensive and easier for respondents to answer, it has quick response time and saves considerable processing effort only the relevant responses are presented based on responses to earlier questions. However, with internet-base surveys the researcher cannot control the target group and surveys do not reflect the general population. To minimize bias and avoid getting multiple responses from the same individual we only allowed one response per computer (by blocking access from the same IP address to the questionnaire). We also tracked the submission times of the completed questionnaires and deleted those with very long completion time. In our study we observed a clear inverse association between increased age and decreased likelihood of response over the Internet. However, we managed to get enough responses for all age groups. To avoid bias with regard to educational background, we included several questions on educational level, professional title, or primary practice setting.

The travel survey data was collected between November $27^{\text {th }}, 2011$ and January $27^{\text {th }}$, 2012 during a series of planned strikes in the Athens subway system. Surveyed travelers were those mostly affected by transit strikes and were visiting transit related websites in order to get information regarding current or future disruptions of the public network ${ }^{2}$ ( $85 \%$ of the respondents stated that their trip has been interrupted by some type of Metro/Tram/Rail closure within the previous 10 days of their travel before the survey). Before releasing the survey, we undertook a pilot survey which provided valuable feedback and led to changes in design, content, attribute definitions, and presentation.

[^12]Information on occupation, frequency of car or PT use was collected in the first part of the survey. Information on recent experience with network disruption during their journey over the last 10 days was collected in the second part. The third part included the SP survey where 9 scenarios were presented to each respondent for various cases of planned subway service disruptions due to strikes. Finally, demographic information was collected including gender, age, employment status, car ownership, income, as well as information on working hour flexibility. A total of 2,359 questionnaires were collected. During the validation of the questionnaires, incomplete questionnaires and questionnaires where travelers were not PT users were omitted from the sample. After removing problematic questionnaires, 1944 ( $82 \%$ of initially collected) remained.

### 6.4.2 Questionnaire Design

The dependent variable in the models developed was the 'mode used during a planned strike' of the Athens Subway. The most important explanatory variables included age, gender, education, main trip purpose, number of times using public transport per week and usual travel time.

The survey was designed as a typical conjoint choice type experiment which intentionally did not consider the presence of a no-choice option because the purpose is to analyze travel patterns under repeated strikes where the available options were limited. Dhar (1997) and Dhar and Simonson (2003) argue that forcing a respondent to make a choice in a conjoint choice experiment might lead to biased parameters when analyzing the choice data. However, in the event of a network disruption, commuters will have no other option but to use one of the given alternatives. The available options considered were the buses, private cars, and taxis. The modes considered cover all available transportation modes within the Athens transport network, except for bicycles and motorcycles. However, the proportion of commuters who use bicycles to commute to work is considerably still low in Athens, and therefore it has not been given as an alternative in the experiment. The experiment did not include the opportunity for telework since the population who teleworks accounts for the less than $2 \%$ of the Athenians. The alternative of either canceling the trip or shifting the departure time was not offered to the respondents as the closure of the subway network seems to be a repeated phenomenon (1-2 per week there is a strike or work stoppage) where it is
impossible to continuously cancel the commute trips. The attributes and attribute levels for each of the options considered by the respondents are presented in Table 6-1.

Table 6-1 Definition of attributes and attribute levels in the Stated Preference Exercise

| Variables | Travel by Bus | Travel by Car | Travel by Taxi |
| :---: | :---: | :---: | :---: |
| In-vehicle-time (minutes) | 25 | 15 | 10 |
|  | 40 | 30 | 25 |
| Total travel costs | 50 | 40 | 35 |
| (euros) | 1.20 | 3.00 | 3.00 |
|  | 1.40 | 5.00 | 7.00 |
| Out-of-vehicle time (minutes) | 2.00 | 8.00 | 12.00 |
| Number of transfers | 10 | 8 | 3 |
|  | 13 | 15 | 5 |
|  | 18 | 20 | 7 |

Within the SP scenarios, three alternatives were offered to respondents who owned a car; car, taxi and bus. For people who did not own a car, bus and taxi were only available. The SP survey was kept relatively simple and included five variables: in-vehicle time, out-ofvehicle time (wait and walk time, parking search time), cost (bus fare, car operating cost, taxi cost) and number of transfers. Attribute levels are explained in detail in Section6.4.3. Most SP surveys have been based on full or fractional designs using orthogonal arrays and thus attributes are independently distributed (Hensher 1994). Our SP design was a conventional fractional factorial orthogonal design which generated 27 SP choices for each segment. To avoid a high task load for each respondent, the 27 SP choices were split into three groups (blocks) of 9 choices for each SP questionnaire. Action available to the respondent in the short-term of a 24 hr Metro strike include: Which mode they would most likely use for their usual commute on the day of the strike? To avoid any ordering bias, the 3 different experiments were presented to each respondent randomly. Table 6-2 shows the fractional factorial design used for the pilot and main study.

Table 6-2 Orthogonal fractional factorial mode-choice experimental design

|  |  | BUS |  |  |  | CAR |  |  | TAXI |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | INVT | FARE | OVT | TRA | INVT | COST | OVT | INVT | COST | OVT |
|  | 1 | 25 | 1,2 | 10 | 0 | 15 | 3 | 8 | 10 | 3 | 3 |
|  | 2 | 40 | 1,4 | 13 | 1 | 30 | 5 | 15 | 25 | 3 | 3 |
|  | 3 | 50 | 2 | 18 | 2 | 45 | 8 | 20 | 35 | 3 | 3 |
| $\sqrt{x}$ | 4 | 50 | 2 | 18 | 1 | 30 | 5 | 8 | 10 | 7 | 5 |
| Oí | 5 | 25 | 1,2 | 10 | 2 | 45 | 8 | 15 | 25 | 7 | 5 |
| ¢ | 6 | 40 | 1,4 | 13 | 0 | 15 | 3 | 20 | 35 | 7 | 5 |
|  | 7 | 40 | 1,4 | 13 | 2 | 45 | 8 | 8 | 10 | 12 | 7 |
|  | 8 | 50 | 2 | 18 | 0 | 15 | 3 | 15 | 25 | 12 | 7 |
|  | 9 | 25 | 1,2 | 10 | 1 | 30 | 5 | 20 | 35 | 12 | 7 |
|  | 10 | 50 | 1,4 | 10 | 2 | 30 | 3 | 20 | 10 | 12 | 5 |
|  | 11 | 25 | 2 | 13 | 0 | 45 | 5 | 8 | 25 | 12 | 5 |
|  | 12 | 40 | 1,2 | 18 | 1 | 15 | 8 | 15 | 35 | 12 | 5 |
|  | 13 | 40 | 1,2 | 18 | 0 | 45 | 5 | 20 | 10 | 3 | 7 |
| U | 14 | 50 | 1,4 | 10 | 1 | 15 | 8 | 8 | 25 | 3 | 7 |
| $\stackrel{0}{\mu}$ | 15 | 25 | 2 | 13 | 2 | 30 | 3 | 15 | 35 | 3 | 7 |
|  | 16 | 25 | 2 | 13 | 1 | 15 | 8 | 20 | 10 | 7 | 3 |
|  | 17 | 40 | 1,2 | 18 | 2 | 30 | 3 | 8 | 25 | 7 | 3 |
|  | 18 | 50 | 1,4 | 10 | 0 | 45 | 5 | 15 | 35 | 7 | 3 |
|  | 19 | 40 | 2 | 10 | 1 | 45 | 3 | 15 | 10 | 7 | 7 |
|  | 20 | 50 | 1,2 | 13 | 2 | 15 | 5 | 20 | 25 | 7 | 7 |
|  | 21 | 25 | 1,4 | 18 | 0 | 30 | 8 | 8 | 35 | 7 | 7 |
| $\cdots$ | 22 | 25 | 1,4 | 18 | 2 | 15 | 5 | 15 | 10 | 12 | 3 |
| 蚍 | 23 | 40 | 2 | 10 | 0 | 30 | 8 | 20 | 25 | 12 | 3 |
| $\frac{0}{9}$ | 24 | 50 | 1,2 | 13 | 1 | 45 | 3 | 8 | 35 | 12 | 3 |
|  | 25 | 50 | 1,2 | 13 | 0 | 30 | 8 | 15 | 10 | 3 | 5 |
|  | 26 | 25 | 1,4 | 18 | 1 | 45 | 3 | 20 | 25 | 3 | 5 |
|  | 27 | 40 | 2 | 10 | 2 | 15 | 5 | 8 | 35 | 3 | 5 |

The main survey data was collected by means of an internet based survey. The reason for conducting an internet based survey was mainly because of the difficulty of contacting travelers who were in some way affected by a Metro disruption. We then realized that we could make use of the websites that were specifically developed to inform passengers on Metro disruptions. Due to the frequency of these closures there exist a sufficient number of websites. After contacting the administrators of these websites, they offered to launch our survey on their websites for a few days. Due to the high number of visitors on the days of strikes we received a quite significant amount of responses in a relative short time. Respondents did welcome the survey and hoped for a solution to their travel problem on the days of strikes.

The complete questionnaire covered a number of topics and was divided in four sections.

Section A: The usual trip and choice of mode for daily activities
Section B: Previous experience of disruptions within the last 10 days of travel with Metro
Section C: Car ownership and SP experiment-criteria of choosing this mode
Section D: Socio-economic questions
The aim of the questionnaire was to collect sufficient data on the travelers' usual trip to determine their work and travel pattern. This section provided information on the regularity of car use and public transport use for commuting purposes which comprised an important input for the choice of mode model. This section was followed by several questions on the journey to work or education for regular commuters. Of note, the respondents of the first section who replied that they never use Public transport were excluded from the survey sample. Travelers were asked to specify the frequency of Subway use and the frequency of car use.

More detailed information on travelers' previous experience of Metro disruption and the way in which they acted was collected from passengers who stated that they had experienced some type of disruption in the last 10 days of their travel. This information was used to provide an understanding of the overall level of awareness of a travel distuption, which assisted in identifying the needs for an information and emergency response system. Travelers were asked to determine the type of the disruption, two available alternative modes of travel, potential cancel of trips or activities, or reschedule of activities due to the disruption.

The fifth section included the SP experiment where respondents were asked to respond to hypothetical questions regarding a 24 hr closure on all Metro lines due to a personnel strike.

### 6.4.3 The Mode-Choice Experiment

The fourth section of the survey also included the refined SP mode-choice experiment. As with the pilot experiment, to initiate the experiment the car ownership status of the individual was established so that the travel choices could be given in a context which had some reality for the respondent.

In participating in the choice experiments, each respondent was asked to consider a context in which the offered set of attributes and levels represented the only available means of
undertaking a commuter trip (for work or educational purposes) from the current residential location to the current workplace. It was made clear that the purpose was to establish the respondents' alternative choice of mode during these circumstances.

Three alternatives appear in each mode choice scenario given to car owners; car, bus and taxi, while only two appear to car non-owners; bus and taxi. The three attributes for the public transport alternative are in-vehicle time, out of vehicle time, fare and number transfer inconvenience. The attributes for taxi are in-vehicle time, out-of-vehicle time and taxi cost and for the car are in-vehicle time, out-of-vehicle time and travel cost. Three levels were selected for each attribute. The design allows for 3 alternatives in the case of carowners and two in the case of car non-owners; car, bus and taxi or bus and taxi. Three alternatives appeared in each travel choice scenario (a) car, (b) bus and (c) and taxi. Twentyseven types of showcards described scenarios involving combinations of travel time, travel cost and transfer inconvenience. Appearance of the pairs was based on experimental design. Attribute levels are summarized in Table 6-1 and an illustrative card is displayed in figure 61.

| SA01 | Bus | Car | Taxi |
| :--- | :--- | :--- | :--- |
| In-vehicle travel time | 15 | 25 | 10 |
| Out-of-vehicle travel time | 10 | 8 | 3 |
| Fuel cost |  | 3.00 |  |
| Taxi cost |  |  | 3.00 |
| Bus ticket | 1.20 |  |  |
| Transfer inconvenience | 1 transfer |  |  |

Figure 6-1 Example of the format of the mode-choice experiment showcard.

The master design of the fractional factorial design produced 27 scenarios or choice sets. The 9 -level factor was used to block the design into 3 versions, each with 9 choice sets containing the three alternatives. Versions were balanced such that each respondent saw every level of each attribute exactly once.

## Detailed Description of attributes

In-vehicle bus Travel time to work/school: There were three different showcards representing short (about 25 minutes), medium (about 40 minutes) and long ( 50 minutes) commutes. These travel times were selected based on real travel time data collected from the RP experiment described in chapter 5.

In-vehicle car Travel time to work/school: Within the set of showcards there were three levels of travel times representing short distances travelled by car (of about 15 minutes drive), medium (of about 30 minutes drive) and long (of about 45 minutes drive).

In-vehicle travel time by taxi: For taxis there were three travel sets to match those of buses and private vehicles. Travel times of 10 minutes represented short-distance trips, travel times of 25 minutes represented medium-distance trips and travel times of 35 minutes represented long distance trips travelled by taxis. Even though these times may be considered quite short compares to the private vehicles and bus travel times, due to the high costs of travelling by taxis, and the flexibility of commuters taxis within a road network without restriction (e.g. due to access restrictions in the city centre-odd and even plate numbers system or due to their right to use the bus lanes) these times are considered quite reasonable for a city like Athens.

Walk/Wait time: The walk/wait time applied only to the bus and taxi alternative. There were three levels of wait time. Walk/Wait time for bus was varied between 10, 13 and 18 minutes to see how sensitive are respondents to long waiting times at the bus stops. Wait time for taxi varied among 3, 5, 7 minutes. These walk/wait times were taken from the Athens Metro Development Study and are based on 2011 records. This time included the walk distance from the respondent's home to the public transport stop in minutes and the wait time for the bus to arrive.

Parking Search Time: This attribute was applied only to car alternative to assess possible changes commuters would make as a response to increasing difficulty in finding a parking spot. Three levels were also used and these were 8 minutes, 15 minutes and 20 minutes.

Taxi cost: Taxi cost gives that total cost of a taxi trip for a certain journey length. Average taxi costs as reported by the travelers in the revealed preference study (analysed in Chapter 5), range from 4.5 euros to 11.3 euros. Since the minimu fare of taxis was 3.00 euros ate the
tiem of survey we assume taxi costs to vary from 3.00, 7.00, and 12.00 euros in our SP experiment.

Car operating cost: This variable gives the operating cost in euros for a single trip. These values are assumed based on the revealed preference survey described in Chapter 5. Based on the results of the study the minimum value for travel time uring the metro closure by car was 30 minutes and the maximum reported was 95 minutes. Average travel speed reported for cars within Athens urban area was $20 \mathrm{~km} / \mathrm{hr}$ in $2009^{1}$. Recent speed measurements on major arterias within Athens urban area showed a maximum 7\% increase in average travel speed between 2009 and $2010^{2}$. This would give us a maximum car travel speed of $21,4 \mathrm{~km} / \mathrm{hr}$. Fuel price per litre at the time of the survey (2011-2012) was 1.64 euros/litre. We assume that fuel price will not exceed 2 euros till 2020 (petrol price will not exceed 100 dollars/barrel) $)^{3}$. Hence we assume that maximum price for fuel will be 1.9 euros/lt. Fuel consumption is assumed to account for the $75 \%$ of the total operating cost and hence the minimum and maximum car operating costs for car based on the travel times reported in the RP survey are:

Table 6-3 Assumptions for car travel cost based on RP survey data

| Travel times <br> reported in RP <br> survey | Average speed | Fuel cost (2011) | Average car fuel <br> consumption | Total travel cost <br> (euros/single <br> trip) |
| :--- | :--- | :--- | :--- | :--- |
| Travel time=30mins | $21.4 \mathrm{~km} / \mathrm{hr}$ | 1.643 euros $/ \mathrm{lt}$ | $0.09 \mathrm{lt} / \mathrm{km}$ | 2.1 euros |
| Travel time $=60 \mathrm{mins}$ | $21.4 \mathrm{~km} / \mathrm{hr}$ | 1.643 euros $/ \mathrm{lt}$ | $0.09 \mathrm{lt} / \mathrm{km}$ | 4.2 euros |
| Travel time=95mins | $21.4 \mathrm{~km} / \mathrm{hr}$ | 1.643 euros $/ \mathrm{lt}$ | $0.09 \mathrm{lt} / \mathrm{km}$ | 6.7 euros |
| Travel time $=95 \mathrm{mins}$ | $21.4 \mathrm{~km} / \mathrm{hr}$ | 1.9 euros $/ \mathrm{lt}$ | $0.09 \mathrm{lt} / \mathrm{km}$ | 7.7 euros |

Based on Table 6-3 we assume travel costs for the one-way commuter trip to vary among 3.00, 5.00 and 8.00 euros.

Bus ticket fare: This variable gives the ticket fare for $1,5 \mathrm{hr}$ trip in euros. This has three levels 1.20 euros, 1.40 and 2.00 euros. 1.20 euros was the current bus fare in 2012.

[^13]
## The sample

The targeted sample was about 2000 questionnaires. A completed interview required the 4 parts of the survey being complete for each respondent including the trip questionnaire, the 10 day experience with disruption, the socio-demographic characteristics part and the SP questionnaire.

A total of 2359 interviews were collected among travelers. Of which only 2008 interviews were entered after the editing process ( $85 \%$ ). Of those 2008 interviews 64 were taken from travelers who stated that they never use Subway. These 64 questionnaires were deliberately removed from the beginning of the survey (they were thanked and were not asked to fill out the rest of the questionnaire) since we are not interested in this category of travelers. Once the questionnaires $(2008-64=1944)$ were completed they went through screening and cleaning process to ascertain the completeness and validity of the responses. At the end of this process we ended up with 1944 questionnaires after removing those interviews with non-sense and irrelevant responses. Questionnaires with lexicographic answers on the SP experiment were also excluded. During the validation of the completed questionnaires, responses that followed some systematic pattern were omitted. Tony Fawkes and Mark Wardman, support that 'identifying and omitting responses which contain serious error or which appear inconsistent with the models to be used can lead to worthwhile improvements in the models developed'.

We ended up with 3 different categories in which to put the questionnaires: (1) incompletes, (2) non regular pt users, (3) incomplete questionnaires in the sp part, (4) incomplete questionnaires in the socioeconomic.

### 6.5 Sample Profile

On average respondents were able to complete the questionnaire in around 10 minutes. Here are some statistics about the sample profile.

Distribution of Survey Time
The share of total respondents with their occupation profile are given in Figure 6-2 and 6-3 for car owners and car non-owners respectively. Of the car-owner population almost $41 \%$ of the respondents were employed full-time, $20 \%$ were self-employed and $31 \%$ were university students.


Figure 6-2 Sample Employment Profile-Car owners

In the non-car owner sample the distribution of employment status is quite different. Only $25 \%$ of the respondents who do not own a car are full-time employed, $9 \%$ self-employed and $58 \%$ university students.


Figure 6-3 Sample Employment Profile-Car non-owners

## Current Journey

Respondents were asked to describe a recent journey that they have undertaken within the last days. The next paragraphs detail how these journeys vary by travel time and mode. Figure 6-4 and 6-5 present the distribution of daily trips for commuting for the RP trips for car ownes and car non-owners respectively.


Figure 6-4 Sample Number of Daily trips for Car owners

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Figure 6-5 Sample Number of Daily trips for Car Non-Owners
In terms of daily trips made by the respondents who own a car, there was a $83 \%$ of the sample who make 1-2 trips a day for commuting purposes. Similar share ( $\sim 78 \%$ ) was found within the car non-owners. Figures 6-6 and 6-7 present the distribution of frequency of Subway use for the selected RP trips for work, education and other purposes.


Figure 6-6 Sample Frequency of Subway Use for Car Owners


Figure 6-7 Sample Frequency of Subway Use for Car Non-Owners

We can see from the two figures that car-owners make less trips with Subway as expected. Students who do not own a car seem to travel quite often with Subway compared to students who do not own a car. $25 \%$ of car owners travel every day by Subway, while this share increases to $56 \%$ for car non-owners.

The following question regarding the usual mode they use for every day trip we did not get the expected results as the respondents could make a multiple choice and in some cases the respondents seem to have described all the possible combinations of modes for their daily trip. For this reason we will not provide the answers for this question.

## Journey duration

Figure 6-8 depicts the journey times in minutes for car owners for commuting purposes.

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Figure 6-8 Usual travel time for commuting-car owners


Figure 6-9 Usual travel time for commuting-Car Non-Owners
For car owners, $32 \%$ of the respondents had journeys between 31 and 45 minutes. As figure 6-8 and 6-9 show a $50 \%$ of the respondents who own a car usually travel between 15
and 45 minutes whereas car non-owners travel longer hours. A $42 \%$ of the respondents who do not own a car travel for more than 45 min , while the respective share of car-owners is only $27 \%$.

A further specification issue that was analyzed was the influence of past choices on choice behavior (Windle \& Dresner, 1995). In the present analysis we had information on the number of times a given traveler used Subway (at least one time per week) in the past 10 days. For each of the $n-1$ alternative modes a coefficient in the utility function was thus associated with the inertia variable related to that alternative. According to Hess (2005), the inclusion of coefficients associated with the inertia variable for one alternative, is also associated with the inertia variable of the remaining alternative.

Hess (2005) expects that the inclusion of these coefficients could lead to problems with endogeneity, as the values of the past choice indicators may be closely correlated with the other explanatory variables and with observables. The author also notes that the dependence on past choices would make this approach inapplicable in the case the model was used for forecasting. Since the values of the remaining coefficients remained largely unaffected the author suggests that the inclusion of these inertia terms did not introduce major bias.

However, forecasting is not the main purpose of the present analysis, we included as inertia term only the number of times a given traveler used Subway (at least one time per week) in the past 10 days and not the number of times a given traveler used the car mode (at least one time per week) in the past 10 days. The reason for this is that our sample is splitted in car owners and car non-owners. Since we have not collected information on the use of taxi and bus, we test the significance of past experience of use of Subway.

Figures 6-10 presents the frequency of car use among respondents for respondents who have car availability. This question makes no sense for car non-owners in terms of car ownership but does make sense in terms of availibility. As we can see from figures 6-11 car non-owners may travel by car as passengers and the biggest share lies in the category of students. $36 \%$ of respondents who own a car, travel every day by car, $22 \%$ travel by car at least 3 times per week, and $23 \%$ of them travel one to twice per week.


Figure 6-10 Frequency of car use within the last 10 days of travel-Car owners

Figures 6-11 and 6-12 present the usage of Subway in a recent trip (within the last 10 days of the survey).


Figure 6-11 Share of CO who used Subway in the last 10 days of their travel


Figure 6-12 Share of NCO who used Subway in the last 10 days of their travel

According to figure 6-11, $60 \%$ of respondents who do not own a car traveled by Subway more than 5 times within the last 10 days of their travel, $\sim 12 \%$ traveled by Subway four times. The share of car owners respondents who traveled by Subway more than 5 times in the last 10 days of their recent trip is $40 \%$, and $7 \%$ travelled 4 times.

## AGE PROFILE

Figure 6-13 shows the age profile of the respondents (car owners) distributed with respect to the modes used.

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Figure 6-13 Age profile wrt usual travel mode (car owners)

Figure 6-14 shows the age profile of the respondents (car non-owners) distributed with respect to the modes used.


Figure 6-14 Age profile wrt usual travel mode (car owners)


Figure 6-15 Age profile wrt to usual travel mode (Car Non-Owners)


Figure 6-16 Income profile wrt to usual travel mode (Car Non-Owners)

Of the total 2022 questionnaires 31 travelers never use Subway modes and 168 did not use Subway in the last 10 days of their travel. There are a number of occurences that can result in an unplanned service disruption, however, these can be broadly categorised according to the following categories as identified during the survey:

- Track related issues, including problems related to power failures, signalling and crossovers
- Rolling stock issues ranging from large infrastructure track works to train failures
- Intrusions/Emergencies-includes protests and riots on the city centre that force the police to close down the entrance to central stations as well as terrorist attacks and suicides.
- Full or partial closure of the Metro line due to personnel strike
- Other reason not reported

Only 1512 ( $85 \%$ ) travelers of a total 2022 reported that they had received information previous to their travel regarding some type of disruption that would affect their usual travel route. The rest $256(15 \%)$ travelers did not receive any information of this type as depicted in Figure 6-17. The sample consists of 1769 travelers and includes both car owners and car non-owners. The rest 199 either did not use Subway in the last 10 days or never use Subway).

Did you receive any information regarding any type of disruptions during your travel?


Figure 6-17 Share of travelers who received some kind of information regarding disruption on their usual travel route

Did you receive any information regarding any type of disruptions during your travel?


Figure 6-18 Causes of service disruptions identified during the survey the last 10 days of their travel

Figure 6-18 highlights the key causes of planned or unplanned service disruptions identified during the survey, as experienced by travelers (car owners and car non-owners) during the last 10 days of their travel. This figure refers only to the travelers who reported that they had experienced some type of disruption during their travel in the last 10 days of their travel. Personnel strike cause is generally more likely to result in a complete line closure while riots and protest in the city centre usually result in a partial line closure or even service delay. The occurrence of suicides often results in the longest delay however passengers are not always informed about the cause of the delay given the need for the police and coroners to be involved (Pender et al., 2012). Pender et al. (2012) continue that service disruptions related to natural or weather disasters can similarly result in long periods of delay; though have never caused the disruption of Subway recently in Athens and especially during the time of the survey. Therefore this cause was not provided as an option in the questionnaire.

We then asked those travelers who reported that had received information previous to their travel regarding some type of disruption whether they cancel any part of their trip. Figure 619 presents the share of travelers who were forced to cancel some part of their trip. This figure shows a substantial high share of travelers cancelling their trip. This emphasizes the size of the problem caused by a disruption in the operation of the Metro system and the importance of this analysis.

Did you cancel any part of your trip?


Figure 6-19 Share of travelers on the question "Did you cancel any part of your trip due to the interrupted Metro operations? (Sample 1512)

A lower share of travelers had to cancel some of their scheduled activities due to the disruption. As shown in Figure 6-20, $73 \%$ of the travelers who experienced a metro closure in the 10 days prior to the day of the survey reported that they decided or were forced to abandon some of their plans for travel due to several reasons such as: car unavailability, low disposal income, fixed arrival time for the specific activity (e.g. doctor's appointment), etc.

Did you cancel any of your scheduled activities?


Figure 6-20 Share of travelers on the question "Did you cancel any of your scheduled activities due to the interrupted Metro operations? (Sample 1512)

Surprisingly high ( $86 \%$ ) is the share of travelers who reported that had to be on their destination on a specific time (Figure 6-21). This question shows that only a limited number of travelers were flexible on schedule. This could be the case of students, younger travelers, tourists, people traveling for leisure or even people who could made flexible working schedule arrangements for that day or could even afford taking annual leave.

Did you have to be on your destination on a specific


Figure 6-21 Share of travelers on the question "Did you have to be on your destination on a specific time on the day of the interrupted Metro operations? (Sample 1512)

### 6.5.1 Altered Travel Patterns during Metro Disruptions

We then asked the travelers to report which available modes of travel they had and which modes they actually chose during the disruption time? The data set used for the case study, consisted of 1527 travelers who reported that experienced some type of disruption in the 10 days of travel before the survey. Travel share profiles, as reported by the travelers during Metro closures faced in the 10 days, before the survey are summarized in Table 6-4. Note here that all available modes were present in this question. Table summarizes travelers' modes and altered travel patterns during any type of Metro disruption ranging from partial Metro closures due to infrastructure works, to all day closures due to personnel strikes. This question only applied to Subway Users, and not travelers who never travel by Subway.

Table 6-4 Table Profile of RP modal share (\%) during Metro disruptions

| Chosen Mode | RP Modal Share |
| :--- | :--- |
| Bike | $3.9 \%$ |
| Taxi | $13.9 \%$ |
| Bus Feeder Line (operating only during disruption) | $0.9 \%$ |
| Metro or Tram or Suburban Rail (Subway Modes) | $5.4 \%$ |
| Bus/Trolley Bus/KTEL | $11.7 \%$ |
| Motorcycle | $3.0 \%$ |
| Car | $32.8 \%$ |
| Cancel activity | $16.2 \%$ |
| Postpone activity | $1.1 \%$ |
| Move to a friend's/relative's house closer to destination | $0.3 \%$ |
| Walk | $8.6 \%$ |
| Carpooling | $0.9 \%$ |
| Other | $1.2 \%$ |
| Total Number | $100 \%$ |
| Note: "Other" is uninformative. |  |

It is evident that a significant share of travelers was forced to cancel or postpone their activities $(17.3 \%)$ due to inability of using alternative modes to the reach their destination. Some travelers reported that the only available alternative they had to travel was rejected for economic reasons. Other reported that they cancelled/missed medical appointments, or took annual leave from work. During the disruption, travelers:

- Adjusted their travel time to avoid congestion, or to travel with a friend/relative
- Postponed/cancel trips
- Walked long distances (some reported over 2 kms )
- Shared travel duties among family members
- Adjusted their residential location to be closer to work destination

It is of particular interest that bike users account for almost $4 \%$ of RP users within the data sample.

The complexity of this phenomenon did not allow us to allocate the various reactions of travelers to each type of disruption, based on the duration and the spread of the disruption on the system (ranging from a few hours to a few days).

### 6.6 Analysis of the Mode Choice SP Exercise

Each respondent saw one SP exercise which was concerned with mode choice and offered a choice between

- Bus-taxi-car for car and Subway users
- Bus-taxi for Subway users who do not own a car

It was agreed to not include other modes as walk or bicycle in the SP exercise as it would lead to an overly complex survey that would be onerous to complete. Bike share is still low in Athens and accounts only for the $3 \%$ of the population ${ }^{1}$.

Figures 6-22 and 6-23 present one example of SP choices presented to the respondent (to car owners and car-owners respectively).


Figure 6-22 Example of mode choice SP card (car users)

[^14]

Figure 6-23 Example of mode choice SP card (non-car users)

This chapter presents the results of the mode choice exercise and the key findings from the SP exercise are presented.

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## Choice proportions

In the following tables (6-5 to 6-21) we present the choice proportions of each mode to understand if the respondents understood the SP exercise and reacted to the proposed trade -off in a sensible way, i.e. the higher cost a service is, the fewer people chose it. The following tables show the percentage of people choosing each option when a change in journey time, cost, and transfer inconvenience occurs and thus the sensitivities to these changes. Each table presents the percentage of respondents choosing one of the three options when either car in-vehicle travel time varies or bus in-vehicle travel time varies or taxi travel time varies.

## Car Owners

Table 6-5 Car owners choice proportions: Varying in-vehicle bus time

| Share (\%) of choice | Bus | Car | Taxi |  |
| :---: | :---: | :---: | :---: | :---: |
| Bus in-vehicle time | \% choosing bus | \% choosing car | \% choosing taxi | Grand Total |
| $\mathbf{2 5}$ | $50 \%$ | $35 \%$ | $15 \%$ | $100 \%$ |
| $\mathbf{4 0}$ | $35 \%$ | $54 \%$ | $12 \%$ | $100 \%$ |
| $\mathbf{5 0}$ | $32 \%$ | $49 \%$ | $20 \%$ | $100 \%$ |

Table 6-6 Car owners choice proportions: Varying bus fare

| Share (\%) of choice | Bus | Car | Taxi |  |
| :---: | :---: | :---: | :---: | :---: |
| Bus fare | \% choosing bus | \% choosing car | \% choosing taxi | Grand Total |
| $\mathbf{2}$ | $37 \%$ | $45 \%$ | $18 \%$ | $100 \%$ |
| 1.20 | $41 \%$ | $47 \%$ | $12 \%$ | $100 \%$ |
| 1.40 | $38 \%$ | $46 \%$ | $16 \%$ | $100 \%$ |

Table 6-7 Car owners choice proportions: Varying out-of-vehicle bus time

| Count of choice | Bus | Car | Taxi |  |
| :---: | :---: | :---: | :---: | :---: |
| Bus out-of-vehicle time | \% choosing bus | \% choosing car | \% choosing taxi | Grand Total |
| $\mathbf{1 0}$ | $44 \%$ | $41 \%$ | $15 \%$ | $100 \%$ |
| $\mathbf{1 3}$ | $35 \%$ | $52 \%$ | $13 \%$ | $100 \%$ |
| $\mathbf{1 8}$ | $37 \%$ | $45 \%$ | $18 \%$ | $100 \%$ |

Table 6-8 Car owners choice proportions: Varying no of transfers within bus trip

| Count of choice | \% choosing bus | \% choosing car | \% choosing taxi |  |
| :---: | :---: | :---: | :---: | :---: |
| No of transfers (bus trips) | Bus | Car | Taxi | Grand Total |
| $\boldsymbol{0}$ | $46 \%$ | $37 \%$ | $16 \%$ | $100 \%$ |
| $\boldsymbol{1}$ | $39 \%$ | $47 \%$ | $14 \%$ | $100 \%$ |
| $\boldsymbol{2}$ | $31 \%$ | $53 \%$ | $16 \%$ | $100 \%$ |

Table 6-9 Car owners choice proportions: Varying car in-vehicle time

| Count of choice | \% choosing bus | \% choosing car | \% choosing taxi |  |
| :---: | :---: | :---: | :---: | :---: |
| Car in-vehicle time | Bus | Car | Taxi | Grand Total |
| $\mathbf{1 5}$ | $27 \%$ | $65 \%$ | $8 \%$ | $100 \%$ |
| $\mathbf{3 0}$ | $39 \%$ | $46 \%$ | $16 \%$ | $100 \%$ |
| $\mathbf{4 5}$ | $52 \%$ | $27 \%$ | $21 \%$ | $100 \%$ |

Table 6-10 Car owners choice proportions: Varying car cost

| Count of choice | \% choosing bus | \% choosing car | \% choosing taxi |  |
| :---: | :---: | :---: | :---: | :---: |
| Car fuel cost | Bus | Car | Taxi | Grand Total |
| $\mathbf{3}$ | $24 \%$ | $67 \%$ | $9 \%$ | $100 \%$ |
| $\mathbf{5}$ | $42 \%$ | $43 \%$ | $15 \%$ | $100 \%$ |
| $\mathbf{8}$ | $50 \%$ | $28 \%$ | $22 \%$ | $100 \%$ |

Table 6-11 Car owners choice proportions: Varying car out-of-vehicle time

| Count of choice | \% choosing bus | \% choosing car | \% choosing taxi |  |
| :---: | :---: | :---: | :---: | :---: |
| Car out-of-vehicle time (PST) | Bus | Car | Taxi | Grand Total |
| $\mathbf{8}$ | $33 \%$ | $54 \%$ | $13 \%$ | $100 \%$ |
| $\mathbf{1 5}$ | $40 \%$ | $46 \%$ | $15 \%$ | $100 \%$ |
| $\mathbf{2 0}$ | $44 \%$ | $38 \%$ | $18 \%$ | $100 \%$ |

Table 6-12 Car owners choice proportions: Varying taxi in-vehicle time

| count of choice | \% choosing bus | \% choosing car | \% choosing taxi |  |
| :---: | :---: | :---: | :---: | :---: |
| Taxi in-vehicle time | Bus | Car | Taxi | Grand Total |
| $\mathbf{1 0}$ | $34 \%$ | $45 \%$ | $22 \%$ | $100 \%$ |
| $\mathbf{2 5}$ | $40 \%$ | $46 \%$ | $15 \%$ | $100 \%$ |
| $\mathbf{3 5}$ | $43 \%$ | $48 \%$ | $9 \%$ | $100 \%$ |

Table 6-13 Car owners choice proportions: Varying taxi fare

| count of choice | \% choosing bus | \% choosing car | \% choosing taxi |  |
| :---: | :---: | :---: | :---: | :---: |
| Taxi cost | Bus | Car | Taxi | Grand Total |
| $\mathbf{3}$ | $29 \%$ | $41 \%$ | $29 \%$ | $100 \%$ |
| $\mathbf{7}$ | $44 \%$ | $45 \%$ | $11 \%$ | $100 \%$ |
| $\mathbf{1 2}$ | $43 \%$ | $51 \%$ | $5 \%$ | $100 \%$ |

Table 6-14 Car owners choice proportions: Varying taxi out-of-vehicle time

| count of choice | \% choosing bus | \% choosing car | \% choosing taxi |  |
| :---: | :---: | :---: | :---: | :---: |
| Taxi out-of-vehicle time | Bus | Car | Taxi | Grand Total |
| $\mathbf{3}$ | $37 \%$ | $48 \%$ | $15 \%$ | $100 \%$ |
| $\mathbf{5}$ | $41 \%$ | $44 \%$ | $15 \%$ | $100 \%$ |
| $\mathbf{7}$ | $38 \%$ | $46 \%$ | $16 \%$ | $100 \%$ |

## CAR NON-OWNERS

Table 6-15 Car non-owners choice proportions: Varying bus in-vehicle time

| Count of choice | \% choosing <br> bus | \% choosing <br> taxi |  |
| :---: | :---: | :---: | :---: |
| Bus in-vehicle time | BUS | TAXI | Grand Total |
| 25 | $78 \%$ | $22 \%$ | $100 \%$ |
| 40 | $69 \%$ | $31 \%$ | $100 \%$ |
| 50 | $60 \%$ | $40 \%$ | $100 \%$ |

Table 6-16 Car non-owners choice proportions: Varying bus fare

| Count of choice | \% choosing <br> bus | \% choosing <br> taxi |  |
| :---: | :---: | :---: | :---: |
| Bus fare | BUS | TAXI | Grand Total |
| 2 | $65 \%$ | $35 \%$ | $100 \%$ |
| 1.20 | $71 \%$ | $29 \%$ | $100 \%$ |
| 1.40 | $69 \%$ | $31 \%$ | $100 \%$ |

Table 6-17 Car non-owners choice proportions: Varying bus out-of-vehicle time

| Count of choice | \% choosing <br> bus | $\%$ choosing <br> taxi |  |
| :---: | :---: | :---: | :---: |
| Bus out-of-vehicle time | BUS | TAXI | Grand Total |
| 10 | $70 \%$ | $30 \%$ | $100 \%$ |
| 13 | $69 \%$ | $31 \%$ | $100 \%$ |
| 18 | $66 \%$ | $34 \%$ | $100 \%$ |

Table 6-18 Car non-owners choice proportions: Varying bus no of transfers

| Count of choice | \% choosing <br> bus | \% choosing <br> taxi |  |
| :---: | :---: | :---: | :---: |
| bus-no of transfers | BUS | TAXI | Grand Total |
| 0 | $71 \%$ | $29 \%$ | $100 \%$ |
| 1 | $69 \%$ | $31 \%$ | $100 \%$ |
| 2 | $65 \%$ | $35 \%$ | $100 \%$ |

Table 6-19 Car non-owners choice proportions: Varying taxi in-vehicle time

| Count of choice | \% choosing <br> bus | \% choosing <br> taxi |  |
| :---: | :---: | :---: | :---: |
| Taxi in-vehicle time | BUS | TAXI | Grand Total |
| 10 | $64 \%$ | $36 \%$ | $100 \%$ |
| 25 | $64 \%$ | $36 \%$ | $100 \%$ |
| 35 | $77 \%$ | $23 \%$ | $100 \%$ |

Table 6-20 Car non-owners choice proportions: Varying taxi fare

| Count of choice | \% choosing <br> bus | \% choosing <br> taxi |  |
| :---: | :---: | :---: | :---: |
| Taxi cost | BUS | TAXI | Grand Total |
| 3 | $42 \%$ | $58 \%$ | $100 \%$ |
| 7 | $74 \%$ | $26 \%$ | $100 \%$ |
| 12 | $88 \%$ | $12 \%$ | $100 \%$ |

Table 6-21 Car non-owners choice proportions: Varying taxi out-of-vehicle time

| Count of choice | \% choosing <br> bus | \% choosing <br> taxi |  |
| :---: | :---: | :---: | :---: |
| Taxi in-vehicle time | BUS | TAXI | Grand Total |
| 10 | $64 \%$ | $36 \%$ | $100 \%$ |
| 25 | $64 \%$ | $36 \%$ | $100 \%$ |
| 35 | $77 \%$ | $23 \%$ | $100 \%$ |

In tables 6-22 and 6-23 below we detail the mode choice proportions as they appear within the data for car owners group and car non-owners group.

Table 6-22 Proportion of times each mode was chosen across all choice sets (CO)

| Car Owners Group (CO) |  |
| :---: | :---: |
| Choice | proportion |
| Bus | 38,88 |
| Car | 45,98 |
| Taxi | 15,14 |

These choice proportions indicate the proportion of times an alternative was chosen across all choice sets (Hensher, Rose and Greene; 2005). From this output it can be seen that the car alternative represents $45.9 \%$ of the choices while the bus alternative was chosen $38.9 \%$ of the time and the taxi alternative was chosen $15.1 \%$ of the time (regardless of scenario).

Table 6-23 Proportion of times each mode was chosen across all choice sets (NCO)

| Car non-owners Group (NCO) |  |
| :---: | :---: |
| Choice | proportion |
| Bus | 68,18 |
| Taxi | 31,83 |

From this output it can be seen that the bus alternative represents 68.2 percent of the choices while the taxi alternative was chosen for 31.8 percent of the choices (regardless of scenario). In our case we use SP data to base these calculations and thus these proportions
indicate the proportion of times an alternative was chosen across all choice sets. Hensher, Rose and Greene (2005) support that since the choice sets are not based upon the real marketplace, but rather upon an experimental design generated by an analyst, these proportions must not be treated as an estimate of the true market shares.

Table 6-24 to 6-27 represent the contingency table produced by NLOGIT, where rows represent the number of choices made by the respondents for each mode, while the columns represent the number of times a mode was predicted to be selected as based on the choice model specified by the author. This prediction is based upon the choice probabilities with the predicted choice corresponding to the mode to which the highest probability is observed (Hensher, Rose and Greene, 2005).

Table 6-24 Actual vs predicted choices -CO

|  | Bus | Car | Taxi | Total |
| :---: | :---: | :---: | :---: | :---: |
| Bus | $\mathbf{1 4 0 5}$ | 1173 | 435 | 3013 |
| Car | 1164 | $\mathbf{1 9 6 5}$ | 434 | 3563 |
| Taxi | 444 | 425 | $\mathbf{3 0 4}$ | 1173 |
| Total | 3013 | 3563 | 1173 | 7749 |

Table 6-25 Actual vs predicted choices
(proportions)-CO

|  | Bus | Car | Taxi |
| :---: | :---: | :---: | :---: |
| Bus | $\mathbf{0 . 4 6 6}$ | 0.389 | 0.144 |
| Car | 0.327 | $\mathbf{0 . 5 5 2}$ | 0.122 |
| Taxi | 0.379 | 0.362 | $\mathbf{0 . 2 5 9}$ |

For the bus alternative, the choice alternative incorrectly predicted $38.9 \%$ of the 3013 choices in which the bus alternative was selected as a choice for the car alternative. The remaining off-diagonal cells reveal where the choice model incorrectly predicted mode choice for the remaining alternatives (Hensher, Rose and Greene, 2005). For car owners, our model correctly predicted the mode chosen $3674(1405+1965+304)$ times out of the total of 7749 choices made.

Thus the overall proportion of correct predictions equals:
$\frac{\text { Number of correct predictions }}{\text { Total number of observations }}=\frac{3674}{7749}=0.47$
Thus for the data, this particular choice model correctly predicted the actual choice outcome for only 47 percent of the total number of cases.

## Car non-owners-Cross tabulation vs predicted choices.

Table 6-26 Actual vs predicted choices -NCO

|  | BUS | TAXI | TOTAL |
| :---: | :---: | :---: | :---: |
| BUS | $\mathbf{4 9 8 0}$ | 1665 | 6645 |
| TAXI | 1665 | $\mathbf{1 4 3 7}$ | 3102 |
| TOTAL | 6645 | 3102 | $\mathbf{9 7 4 7}$ |

Table 6-27 Actual vs predicted choices (proportions)-NCO

|  | BUS | TAXI |
| :---: | :---: | :---: |
| BUS | $\mathbf{0 . 7 4 9}$ | 0.537 |
| TAXI | 0.251 | $\mathbf{0 . 4 6 3}$ |

For car non-owners, our model correctly predicted the mode chosen 6417 (4980+1437) times out of the total of 9747 choices made. Thus the overall proportion of correct predictions equals
$\frac{\text { Number of correct predictions }}{\text { Total number of observations }}=\frac{6417}{9747}=0.66$
Thus for the data, this particular choice model correctly predicted the actual choice outcome for only 66 percent of the total number of cases.

Within the contingency table produced by NLOGIT the rows represent the number of choices made by those sampled for each alternative, while the columns represent the number of times an alternative was predicted to be selected as based on the choice model specified by the analyst. The diagonal elements of the contingency table represent the
number of times the choice model correctly predicted the choice of alternative as observed in the data.

Tables 6-28 and 6-29 also include detailed common traveler characteristics such as, for example, 'How often do you use subway', or 'How long is your commute to work', for sample of car-owners and non car-owners respectively. Since not all respondents use the subway with the same frequency, an assumption that the behavioral patterns of all individuals follow the same trend would be restrictive. Each respondent saw every level of each attribute exactly once.

In the case of categorical variables sex, age, trip purpose, income, frequency of subway use, working flexibility and usual travel time to work we use dummy variables to contrast the different categories (k). For each dummy variable we choose a base line category and contrast the remaining ( $k-1$ ) variables with the base line category.

Table 6-28 Sample characteristics-travelers owning a private vehicle

| Variable | Type | Statistics | (\%) | Description |
| :---: | :---: | :---: | :---: | :---: |
| Male | Dummy | $\mathrm{F}(1)=495$ | (57\%) | $=1$ if male |
|  |  | $F(0)=366$ | (43\%) | $=0$ if female |
| Age18-34 | Dummy | $F(1)=621$ | (72\%) | $\begin{aligned} & =1 \text { if respondent's age } \\ & >=18 \text { and }<=34 \end{aligned}$ |
|  |  |  |  | $=0$ if not |
| Age35-44 | Dummy | $F(1)=156$ | (18.1\%) | $\begin{aligned} & =1 \text { if respondent's age } \\ & >=35 \text { and }<=44 \end{aligned}$ |
|  |  |  |  | $=0$ if not |
| Age45-54 | Dummy | $F(1)=64$ | (7.4\%) | $\begin{aligned} & =1 \text { if respondent's age } \\ & >=45 \text { and }<=54 \end{aligned}$ |
|  |  |  |  | $=0$ if not |
| Age55+ | Dummy | $F(1)=20$ | (2.3\%) | $\begin{aligned} & =1 \text { if respondent's age } \\ & >55 \end{aligned}$ |
|  |  |  |  | $=0$ if not |
| Work | Dummy | $\mathrm{F}(1)=528$ | (61\%) | $=1$ if working |
|  |  | $F(0)=333$ | (39\%) | $=0$ if not |
| Low_Income | Dummy | $\mathrm{F}(1)=375$ | (44\%) | $=1$ if $<800$ euros |
|  |  |  |  | $=0$ if not |
| Med_Income | Dummy | $F(1)=291$ | (34\%) | $=1$ if <801-1500 euros |
|  |  |  |  | $=0$ if not |
| High_Income | Dummy | $F(1)=195$ | (22\%) | $=1$ if $>1501$ euros |
|  |  |  |  | $=0$ if not |
| Subway Users | Dummy | $\begin{aligned} & F(1)=644 \\ & F(0)=217 \end{aligned}$ | $\begin{aligned} & (75 \%) \\ & (25 \%) \end{aligned}$ | $=1$ if they use subway at |
|  |  |  |  | least 1-2 times per week or more |
|  |  |  |  | $=0$ if they use subway less than once per week |
| Usual Travel Time to work/School | Categorical | $F(1)=328$ | (38\%) | $=1$ if 5-30 minutes |
|  |  | $\mathrm{F}(2)=275$ | (32\%) | $=2$ if 31-45 minutes |
|  |  | $F(3)=156$ | (18\%) | $=3$ if 46-60 minutes |
|  |  | $F(4)=102$ | (12\%) | $=4$ if $>60$ minutes |
| Flexible working | Dummy | $F(1)=418$ | (49\%) | $=1$ if they have flexible |
|  |  | $F(0)=443$ | (51\%) | working hours |
|  |  |  |  | $=0$ if they do not have flexible working hours |

Table 6-29 Sample characteristics-travelers not-owning a private vehicle

| Variable | Type | Statistics | (\%) | Description |
| :---: | :---: | :---: | :---: | :---: |
| Male | Dummy | $F(1)=427$ | (39\%) | $=1$ if male |
|  |  | $F(0)=656$ | (61\%) | $=0$ if female |
| Age18-34 | Dummy | $F(1)=970$ | (89\%) | $\begin{aligned} & =1 \text { if respondent's age } \\ & >=18 \text { and }<=34 \end{aligned}$ |
|  |  |  |  | $=0$ if not |
| Age35-44 | Dummy | $F(1)=87$ | (8\%) | $\begin{aligned} & =1 \text { if respondent's age } \\ & >=35 \text { and }<=44 \end{aligned}$ |
|  |  |  |  | $=0$ if not |
| Age45-54 | Dummy | $F(1)=17$ | (2\%) | $\begin{aligned} & =1 \text { if respondent's age } \\ & >=45 \text { and }<=54 \end{aligned}$ |
|  |  |  |  | $=0$ if not |
| Age55+ | Dummy | $F(1)=9$ | (1\%) | $\begin{aligned} & =1 \text { if respondent's age } \\ & >55 \end{aligned}$ |
|  |  |  |  | $=0$ if not |
| Work | Dummy | $F(1)=368$ | (34\%) | $=1$ if working |
|  |  | $\mathrm{F}(0)=715$ | (66\%) | $=0$ if not working |
| Low _Income | Dummy | $F(1)=806$ | (74\%) | $=1$ if $<800$ euros |
|  |  |  |  | $=0$ if not |
| Medium_Income | Dummy | $F(1)=239$ | (22\%) | $=1$ if <801-1500 euros |
|  |  |  |  | $=0$ if not |
| High_Income | Dummy | $F(1)=38$ | (4\%) | $=1$ if $>1501$ euros |
|  |  |  |  | $=0$ if not |
| Subway users | Dummy | $F(1)=904$ | (83\%) | $=1$ if they use subway at |
|  |  | $\mathrm{F}(0)=179$ | (17\%) | least 1-2 times per week or more |
|  |  |  |  | $=0$ if they use subway less than once per week |
| Usual Travel Time to Work/school | Categorical | $\mathrm{F}(1)=300$ | (28\%) | $=1$ if 5-30 minutes |
|  |  | $F(2)=316$ | (37\%) | $=2$ if 31-45 minutes |
|  |  | $F(3)=281$ | (33\%) | $=3$ if 46-60 minutes |
|  |  | $\mathrm{F}(4)=186$ | (22\%) | $=4$ if $>60$ minutes |
| Flexible working | Binary | $F(1)=580$ | (54\%) | $=1$ if they have flexible |
|  |  | $F(0)=503$ | (46\%) | working hours |
|  |  |  |  | $=0$ if they do not have flexible working hours |

### 6.7 Model Estimation

### 6.7.1 Partially-Specified Models

An important question arises with regards to the specification of the constants in the model. Since we deal with a one-dimensional choice process, a single alternative specific constant (ASC) is associated with each alternative, with all but one of the constants being estimated. While it is in theory possible to further improve the specification by using a separate parameter for each level of the e.g. income group or for each level of another SDC variable associated with travel time, cost or transfer inconvenience, we assume that this process would not offer any significant improvement in LL.

Analyses were undertaken separately depending on the ownership for the respondents, since the car was not offered as an alternative option to travelers who reported not owning a private vehicle. For each dataset, we tested the differences between MNL, MNP and HEV models. The first model incorporated only variables related to the transport system: travel time (in-vehicle time and out-of-vehicle time), fare, and the number of transfers within the journey (Table 6-30); this model is termed as partiallyspecified.

Table 6-30 Partially-specified Logit and Probit results for travelers

| Variables | Travelers owning private vehicle |  | Travelers not owning travel vehicle |  |
| :---: | :---: | :---: | :---: | :---: |
|  | MNL ${ }^{\text {a }}$ | MNP ${ }^{\text {a }}$ | Binomial Logit ${ }^{\text {b }}$ | Binomial Probit ${ }^{\text {b }}$ |
|  | coefficient (t-stat) | coefficient (t-stat) | coefficient (t-stat) | coefficient (t-stat) |
| In-vehicle time | -0.038 (-24.64) | -0.031(-20.26) | -0.038 (-21.09) | -0.032(-21.10) |
| Cost | -0.211 (-25.36) | -0.155 (-23.26) | -0.292 (-37.96) | -0.239 (-41.35) |
| Out-of-vehicle time | -0.039 (-9.21) | -0.034 (-9.34) | -0.038 (-5.30) | -0.031 (-5.38) |
| Number of transfers | -0.236 (-7.69) | -0.200 (-7.36) | -0.188 (-6.20) | -0.158 (-6.29) |
| ASC_bus | 1.057 (12.88) | 0.78 (12.5) | 0.457 (5.11) | 0.396 (5.37) |
| ASC_car | 1.525 (25.92) | 1.08 (18.88) | N/A | N/A |
| Null loglikelihood LL(0) | -7829.10 | -7829.10 | -6097.18 | -6097.18 |
| Final loglikelihood | -6765.46 | -6756.81 | -4991.20 | -4996.59 |
| Likelihood ratio test | -2127.27 | -2144.58 | -2211.96 | -2201.18 |
| Adjusted R-square $\text { ( } \varrho_{2} \text { ) }$ | 0.136 | 0.206 | 0.181 | 0.260 |

${ }^{\text {a }} \mathrm{N}=861$ respondents ; Sample size for MNL model refers to individuals (each providing 9 responses), number of observations is 7749 .
${ }^{\mathrm{b}} \mathrm{N}=1083$ respondents; Sample size for MNL model refers to individuals (each providing 9 responses), number of observations is 9747.
N/A non-applicable

## Multinomial Logit model for car owners and car non-owners

The estimation dataset for car owners contains information on 7749 observations, whereas the estimation dataset for car non-owners contains information on 9747 observations. The process revealed significant negative effects of in-vehicle travel time, out-of vehicle travel time, transfer inconvenience and travel cost.

Initial results confirm that for travelers who own a private vehicle, the alternative specific constant for car is positive and higher than the one for bus, indicating that all else being equal, car is the most preferable choice. For both car-owners and car non-owners all coefficient estimates have the expected sign and are consistent with a-priori assumptions (Hensher 2001). Negative signs for time, cost and number of extra transfers within a
journey indicate that an increase in travel time, cost or number of transfers will reduce the utility (and thus the chosen probability) of an alternative.

The number of transfers variable for car-owners and car non-owners is negative and significant. The magnitude of the coefficient of transfer variable is higher than cost which suggests that car-owners are less sensitive to an increase in gas price than they are for an additional transfer. The magnitude of the coefficient of transfer for car nonowners is less than cost, which indicates that car non-owners are more sensitive to an increase in ticket cost than to an increase in the number of transfers to complete their journey. The coefficients for in-vehicle and out-of-vehicle times are negative and highly significant for car and bus.

## Multinomial Probit model for car owners and car non-owners

The estimation dataset for car owners contains information on 7749 observations, whereas the estimation dataset for car non-owners contains information on 9747 observations. Both the Logit and Probit models indicate that travelers are equally sensitive to travel time whether they walk or wait at the bus stop, or search for parking.

There are no significant differences between the Logit and Probit models estimated on the same data set. It is important to note however, that the Probit model is computationally more demanding than the MNL model both in terms of evaluation and estimation (Munizaga et al. 2000). Overall, estimation results indicate the viability of the MNL and MNP models in testing SP choice experiments. Although there are no general rules to evaluate goodness-of-fit (rho-square values), it can be argued that the values are acceptable and that the probit models are superior to Logit in terms of rho-square.

## Estimating Value of Travel Time Savings (VTTS)

In this section we compute the value of Travel Time Savings (VTTS), defined as the amount of money an individual is willing to pay in order to save a unit of time spent travelling. The computation of VTTS measures has been one of the main applications of random utility models, with some discussions on the topic including Algers et al. (1998), Hensher (2001a,b,c), and Cirillo and Axhausen (2004) (in Hess et al, 2004).

In discrete choice models, the computation of VTTS measures is to be calculated as the ratio of the partial derivatives of the utility function with respect to travel time and travel
cost (Hensher, 2005). The VTTS in the case of an MNL model may be calculated as follows:

VTTS $=\frac{\beta_{\text {time }} * 60}{\beta_{\text {cost }}} 60$

We multiplied the VTTS measure by 60 to give a measure of VTTS in euros per hour rather than euros per minute.

It is important to note here that both attributes of time and cost need to be statistically significant in order to calculate the VTTS, otherwise no meaningful Willingness to Pay measure can be established.

As such, the VTTS from the above model may be calculated as follows for car owners:

$$
V T T S_{\text {car owners }}=\frac{\beta_{\text {time }}}{\beta_{\text {cost }}} \times 60=\frac{(-0.038)}{(-0.211)}=10.8 \frac{\text { euros }}{\mathrm{hr}}
$$

Whereas for car non-owners is:

$$
V T T S_{\text {car owners }}=\frac{\beta_{\text {time }}}{\beta_{\text {cost }}} \times 60=\frac{(-0.038)}{(-0.292)}=7.8 \frac{\text { euros }}{\mathrm{hr}}
$$

A useful manner by which to compare models is the mean estimate of direct elasticity. This provides direct evidence regarding the relative sensitivity of each model with respect to modal shares associated with a change in the level of a specific trip attribute (Greene and Hensher 2010). Table 6-31 shows the elasticities with respect to a change of generic attributes such as travel time, fare and transfer inconvenience for the Multinomial Logit and Probit models of car-owners and non car-owners respectively.

Table 6-31 Direct Time, Cost and Transfer Elasticities during a programmed subway closure

| closure |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Travelers owning private vehicle |  |  |  | Travelers not owning travel vehicle |  |  |  |
|  | MNL ${ }^{\text {a }}$ |  | MNP ${ }^{\text {a }}$ |  | Binomial Logit ${ }^{\text {b }}$ |  | Binomial Probit ${ }^{\text {b }}$ |  |
| Attribute | Mean1 | St. Dev2 | mean | St. Dev | mean | St. Dev | mean | St. Dev |
| Bus demand wrt to in-vehicle travel time | -0.929 | 0.43 | -0.953 | 0.48 | -0.502 | 0.39 | -0.496 | 0.361 |
| Bus demand wrt to in-vehicle travel time | -0.709 | 0.48 | -0.671 | 0.47 | N/A | N/A | N/A | N/A |
| Taxi demand wrt to in-vehicle travel time | -0.787 | 0.39 | -1.117 | 0.66 | -0.630 | 0.38 | -0.697 | 0.47 |
| Bus demand wrt fare cost | -0.199 | 0.08 | -0.182 | 0.08 | -0.145 | 0.11 | -0.139 | 0.09 |
| Car demand wrt to fuel consumption | -0.690 | 0.46 | -0.596 | 0.42 | N/A | N/A | N/A | N/A |
| Taxi demand and general travel cost | -1.380 | 0.80 | -1.90 | 1.34 | -1.661 | 1.17 | -1.830 | 1.46 |
| Bus demand wrt wait and walk time | -0.330 | 0.14 | -0.362 | 0.16 | -0.168 | 0.125 | -0.161 | 0.11 |
| Car demand wrt to parking search time | -0.321 | 0.19 | -0.326 | 0.20 | N/A | N/A | N/A | N/A |
| Taxi demand wrt to wait and walk time | -0.169 | 0.06 | -0.257 | 0.12 | -0.131 | 0.06 | -0.138 | 0.08 |
| Bus demand wrt to transfer inconvenience | -0.157 | 0.14 | -0.165 | 0.15 | -0.063 | 0.08 | -0.063 | 0.74 |

${ }^{\text {a }} \mathrm{N}=861$ respondents ; Sample size for MNL model refers to individuals (each providing 9 responses), number of observations is 7749 .
${ }^{\mathrm{b}} \mathrm{N}=1083$ respondents; Sample size for MNL model refers to individuals (each providing 9 responses), number of observations is 9747 .
${ }^{1}$ Mean estimate of direct elasticity
${ }^{2}$ Standard Deviation
N/A non applicable
Results suggest that a $10 \%$ increase in bus travel time during a subway closure would result in a $9 \%$ reduction in the car owner travelers who selected it as their alternative. Car non-owners though are less sensitive to bus travel time during a subway closure compared to car owners (elasticity of -0.5 ). Similarly, results suggest that a $10 \%$ increase in taxi travel time during a subway closure would result in a 6-7\% reduction in the travelers who selected it as their alternative.

Interestingly, car choice during a subway closure is not sensitive to parking search time (elasticity of -0.3). On the other hand, car non-owners seem less sensitive to deterioration of the public transit service; if bus headways increase, bus patronage would drop by only $1.7 \%$ during closures.

Similarly, a $10 \%$ increase in fuel consumption due to congested roads and increased travel times would result in a $7 \%$ reduction (logit) in the car owner travelers who selected it as their alternative. We note that elasticities of car demand with regard to fuel consumption and relative cost during closures appear higher compared to average shortrun elasticity values and closer to average long-run elasticities reported in the literature (Goodwin 1992; de Jong and Gunn 2001). As expected, public transport demand is less
sensitive to cost changes (elasticity of -0.2 ) during a subway closure, while car demand is much more sensitive to a potential change in gas price.

### 6.7.2 Fully-Specified Model

The next step was to add a set of socio-demographic variables (age, income, gender, flexibility in working hours) and trip-related variable (purpose) to each of the selected models in each of the above mentioned data sets. Tables 6-32 and 6-33 present the results of the fully specified models incorporating trip related and traveler related variables using Logit, Probit and HEV models.

Table 6-32 Fully-Specified MNL, MNP and HEV results for car owners

| Model | Logit ${ }^{\text {a }}$ |  | Probit ${ }^{a}$ |  | $\mathrm{HEV}^{\text {a }}$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Utility parameter name | coefficient | t-stat | coefficient | t-stat | coefficient | t-stat |
| BUS |  |  |  |  |  |  |
| Constant Bus | 0.959 | 3.47 | 0.66 | 3.62 | 1.011 | 3.47 |
| Age:18-35 | n/ |  | n/ |  | -0.419 | -1.685 |
| Age:35-45 | n/ |  | $\mathrm{n} /$ |  | -0.566 | -2.20 |
| Income: High | -0.289 | -2.79 | -0.207 | -2.92 | -0.347 | -2.30 |
| Income: Low | $\mathrm{n} / \mathrm{s}$ |  | $\mathrm{n} / \mathrm{s}$ |  | 0.249 | 2.06 |
| Usual Travel time :46-60 mins | 0.276 | 2.57 | 0.205 | 2.74 | 0.348 | 2.87 |
| Usual Travel time : $>=60 \mathrm{mins}$ | 0.766 | 5.89 | 0.527 | 5.80 | 0.885 | 6.09 |
| Use subway at least <br> once per week 0.337 3.64 0.246 3.75 0.405 3.77 |  |  |  |  |  |  |
| CAR |  |  |  |  |  |  |
| Constant Car | 1.419 | 5.00 | 0.947 | 4.45 | 1.327 | 3.77 |
| Gender: Male | 0.216 | 2.88 | 0.172 | 3.15 | 0.269 | 2.99 |
| Age:18-35 | 0.713 | 2.74 | 0.665 | 3.48 | 0.978 | 3.03 |
| Age:35-45 | 0.573 | 2.16 | 0.566 | 2.90 | 0.789 | 2.41 |
| Age:45-55 | $\mathrm{n} / \mathrm{s}$ |  | 0.496 | 2.43 | $\mathrm{n} / \mathrm{s}$ |  |
| Trip purpose: Work | -0.239 | -2.12 | -0.194 | -2.40 | -0.263 | -1.99 |
| Use subway at least once per week | -0.497 | -5.62 | -0.423 | -6.39 | -0.696 | -6.08 |
| Flexible working hours | $\mathrm{n} / \mathrm{s}$ |  | -0.116 | -2.02 | $\mathrm{n} / \mathrm{s}$ |  |
| In-vehicle time | -0.041 | -25.34 | -0.032 | -19.94 | -0.052 | -14.84 |
| Cost | -0.220 | -25.55 | -0.158 | -23.38 | -0.257 | -20.14 |
| Out-of-vehicle-time | -0.041 | -9.44 | -0.034 | -9.52 | -0.055 | -8.36 |
| Number of transfers | -0.255 | -8.08 | -0.199 | -7.62 | -0.315 | -6.91 |
| Null Log-Likelihood | -7829.10 |  | -7829.10 |  | -7829.10 |  |
| Final log-likelihood | -6537.45 |  | -6531.71 |  | -6526.57 |  |
| Likelihood ratio test | -2583.31 |  | -2594.78 |  | -2605.06 |  |
| Rho-square (e2) | 0.165 |  | 0.233 |  | 0.233 |  |

$\mathrm{n} / \mathrm{s}$ Not significant at $10 \%$ level
${ }^{\text {a }} \mathrm{N}=861$ respondents; sample size for MNL model refers to individuals (each providing 9 responses), number of observations is 7749 .

It is evident from Table 6-32 that the fit is lower for the logit model compared to probit and HEV. In the HEV model, all parameters are significant and with the expected signs. Parameter differences between income, travel time, age, use of Subway, in-vehicle time, cost and transfer inconvenience are significant between model specifications. Results also indicate that the effect of the attributes on the model accuracy differs between variables, with probit models producing the lower coefficients (in absolute values), and heteroskedastic model producing the higher coefficients (in absolute values).

Table 6-33 Fully-Specified MNL, MNP and HEV results for car non-owners

| Model | Logit ${ }^{\text {a }}$ |  | Probit ${ }^{\text {a }}$ |  | $\mathrm{HEV}^{\text {a }}$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Utility parameter name | coefficient | t-stat | coefficient | t-stat | coefficient | t-stat |
| BUS |  |  |  |  |  |  |
| Constant Bus | 0.787 | 2.52 | 0.559 | 2.62 | 0.816 | 3.33 |
| Gender: Male | 0.391 | 7.57 | 0.323 | 7.48 | 0.335 | 7.09 |
| Age:18-35 | -0.693 | -2.34 | -0.504 | -2.40 | -0.611 | -2.60 |
| Age:35-45 | -0.711 | -2.34 | -0.493 | -2.24 | -0.640 | -2.64 |
| Age:45-55 | -0.878 | -2.55 | -0.638 | -2.50 | -0.777 | -2.84 |
| Income: High | -0.460 | -3.36 | -0.383 | -3.58 | -0.372 | -3.48 |
| Income: Low | 0.526 | 8.20 | 0.453 | 8.60 | 0.421 | 7.27 |
| Usual travel time:46-60 mins | 0.149 | 2.16 | 0.122 | 2.08 | 0.131 | 2.18 |
| Usual travel time: $>=60$ mins | 0.194 | 2.48 | 0.150 | 2.32 | 0.182 | 2.71 |
| In-vehicle time | -0.039 | -20.99 | -0.032 | -20.88 | -0.034 | -17.30 |
| Cost | -0.299 | -37.90 | -0.245 | -41.46 | -0.271 | -23.62 |
| Out-of-vehicle-time | -0.039 | -5.36 | -0.032 | -5.39 | -0.032 | -5.08 |
| Number of transfers | -0.193 | -6.29 | -0.161 | -6.31 | -0.154 | -5.501 |
| Number of observations | 9747 |  | 9747 |  | 9747 |  |
| Null Log-likelihood | -6097.18 |  | -6097.18 |  | -6097.18 |  |
| Log-likelihood | -4891.29 |  | -4894.78 |  | -4886.75 |  |
| Likelihood ratio test | -2411.79 |  | -2404.8 |  | -2420.86 |  |
| Rho-square (@2) | 0.198 |  | 0.276 |  | 0.277 |  |

$\mathrm{n} / \mathrm{s}$ Not significant at $10 \%$ level
$\mathrm{N}=1083$ respondents; sample size for MNL, MNP, HEV model refers to individuals (each providing 9 responses), number of observations is 9747.

We note that the three models provided similar results regarding the significance of the independent variables and the coefficient signs. The positive sign for 'male' suggests that male car owners spend more time driving than traveling on the bus during a subway closure. The age variable is alternative specific; car-owners between 18 and 35 appear to drive more often during a closure than other age groups. Travelers who usually travel more than 45 minutes (Tables 6-32 and 6-333) are more attracted to the bus during closures. As we can see from Table 6-33, the coefficient of 'usual travel time (>45 minutes)' is positive and highly significant for bus users. This finding is reasonable since
travelers, and particularly commuters, usually drive for shorter distances during subway closures.

The coefficient for 'transfer' for car owners is 6 times higher than that of travel time (either in-vehicle or out-of-vehicle time), indicating that car owners are more likely to object to additional boarding on different modes during a subway closure compared to travelling longer or paying more. For car non-owners though, travel time is less significant than transfer and cost during a subway closure. Car non-owners have a lower value for time than car-owners, and value more the cost of public transport than carowners. These findings indicate that car non-owners derive the highest benefit from a reduction in bus fare during a subway closure. Travelers who use subway regularly would use bus in the event of a programmed closure of the subway network, while travelers who usually travel by modes other than subway, would use the car. Commuters who own a car seem to be more willing to drive in the event of a closure than other travelers.

Low income travelers who own a car tend to use bus more during subway closures, while the income variable was found to be non-significant for car users. This is expected, as low income travelers usually prefer public transportation modes during closures for longer distances due to financial constraints. Flexibility of working hours was found to be statistically significant only for car owners, indicating that travelers who are flexible with arrival and departure time are less likely to choose car-related modes during a subway closure, while travelers with inflexible hours are restricted to using a car in the event of a subway closure.

### 6.8 Conclusions

This study offers an analysis of traveler responses to a programmed subway closure due to personnel strike. Multinomial Logit, Probit and HEV models were built to better understand the choice of model for travelers during a strike. Both HEV and MNP relax the irrelevant alternatives property of the MNL model, which is a crucial consideration. Socio-demographic variables (age, income, gender, flexibility in working hours) and triprelated variable (purpose, usual travel time) were among the variables discussed. All models had similar results on the significance of age, gender and income. Results indicated that travelers who are regular subway travelers and have therefore been more affected by network disruptions, are less likely to shift to the car as a result of that disruption. Younger travelers (age $<35$ years) are more likely to change their travel patterns. The results also showed that travelers between 45 and 55 will shift to using a
car regardless of the increased travel time or cost during a closure. Regular subway travelers are more likely to use other public transportation alternatives rather than shifting to the car during a programmed closure. The mean in-vehicle travel time elasticity for bus users is found to be -0.9 , for car-owners during a subway closure, while for car non-owners is -0.5 .

The travel patterns during a subway closure depend on their individual socioeconomic and trip related characteristics. Our research shows that those travelers who are flexible with arrival and departure times at their destination, would travel by public transport during a closure. For travelers who are not flexible in terms of time our research indicates that they would consider using their private vehicle during a closure. One limitation of this study is the relative small size of travelers aged over 55 years old. Further research should be aimed at collecting larger data sets, possibly relying on social network sources. We also note the possible importance of using technologies such as GPS and Bluetooth devices to collect representative data; as Zhu and Levinson (2011) note, objective observations of travel decisions and experience such as route selected, departure time, travel speed, and on-route delay from GPS devices could supplement subjective evaluations collected from existing surveys, and thus allow for more sophisticated behavioral analyses.

The results of our questionnaire can shed light on traveler experiences during a closure and on the strategies people adopt when experiencing a disruption. This study is intended to provide a reasonable starting point for travel demand modeling in specific situations of subway closures. Models similar to the ones developed here can prove valuable when planning the delivery of subway upgrades and alternative transport options when lines are closed. Municipalities and transit authorities should learn from past experience and provide options (teleworking, carpooling, free or discounted transit passes, etc) and have contingency plans to make traffic smoother for commuters, based on results presented.

Though the variable of flexible working schedule was not found significant for all users and between all tested models, we still believe that this is an important factor related to anyone's decision regarding mode choice. "Telework" is defined as a form of organizing and/or performing work, using information technology, in the context of an employment contract/relationship, where work, which could also be performed at the
employer's premises, is carried out away from those premises on a regular basis (European Framework Agreement on Telework ${ }^{1}$ ).

The concept of telework although new, is clearly growing in the European Union of the 27 countries (European Foundation for the Improvement of Living and Working Conditions, 2010). Given the growing need of dealing with the effects of subway closures we suggest the implementation of such a scheme in the event of disruptions.

If travelers are given the option of canceling their commuting trip to work, instead work from home, this would possibly change the mode shares during a subway closure. Even the possibility of flexible working schedule may lead some travelers to either walk to their destination if not on a hurry, or ride their bicycle or even try car-pooling with others. In the case of inflexible working schedule travelers may be forced to pay extra to arrive on schedule to their working location.

Since this question on the survey was not applicable for all travelers (either because not all of the surveyed population is employed or because some students are flexible with schedule) we cannot reach stable conclusions. Although telework cannot be promoted during all types of disruptions especially when these last longer than a few days or when these disruption are a result of a sudden breakdown, it is considered that it does result in less traffic on congested highways during the peak hours. Lari (2012) analyzed the results of a major initiative of telework in Minnesota. The author summarizes the positive results of this initiative through reduction in peak-period trips taken and vehicle miles traveled. Among the benefits of telework, as reported by the author we focus on the most relevant ones to our study (Lari, 2012):

- Improvement in emergency responsiveness and continuity of operations
- Reduction of vehicle tear-and-wear, congestion and commuting time
- Benefits reflected in different aspects of life; economically, psychologically, socially
- Operating cost savings
- Improved employee performance

[^15]Ott et al. (1980), studied the effect of flextime on travel behavior, traffic congestion and energy consumption. According to their study, individuals who have longer travel times, and use transit have later mean arrivals, those who have higher numbers of children and who are older have earlier arrivals. Based on the same study, a majority of workers experienced savings in travel time due to flextime.

Jovanis et al. (1984), support that workplace constraints are important because of the probability of a "preferred" arrival time, despite flextime, the worker can feel subtle (or not so subtle) expectations from their supervisors concerning a desirable arrival time. Owen (1979) concludes that the worker may feel increased utility for a specific arrival time because he can impress supervisors with his punctuality (Paul et al., 1984).

## 7. Joint RP-SP Analysis

### 7.1 Introduction

This chapter formulates and applies a nested logit framework for joint analysis of RP and SP data that accommodates heterogeneity across individuals in the responsiveness to level-of-service factors, scale difference in the revealed and stated choice contexts. As discussed in Chapters 5 and 6, part of this research included collecting RP data related to the behavior response of metro travelers to a 5 -month partial closure of Metro Line 1 and SP data related to the choice of mode of travelers in the hypothetical event of a 24 hr subway closure. The RP data has already been used in this dissertation to build a binary logit model of alternative travel patterns during metro closure, while the SP data has been used to build a MNL, a MNP and a HEV model of alternative travel pattern in the case as a result of 24 hr disruptions in operation of subway network. The detailed analysis of the models' development is presented in Chapters 5 and 6 respectively.

The results indicated that using only RP data results in a statistically insignificant trip purpose coefficient during a partial closure of the metro network, reflecting inability of collecting trip information related to the non-chosen alternative mode within the RP sample, as well as inability to collect data related to cost and sociodemographic characteristics. On the other hand, SP data and other hypothetical data are particularly useful when RP data do not have sufficient variation in attributes or too much correlation among the attributes (Mabit, 2010). However, the alternative-specific constants produced from the SP experiment are not reflective of the market shares of the alternatives. The initial results of our separate analysis of RP and SP data indicate substantial variation (or unobserved heterogeneity) across individuals, and resistance to change travel mode. Since past frequency of subway resulted in a higher probability of using the bus in the event of a subway network disruption, one would expect resistance to change of travel mode during closure. However, frequent car use did not result in higher shares of travelers choosing the car mode as an alternative to the 5-month Metro closure.

Since past behavior frequently regulates a new decision context, combining two sources of data - one of actual experience and one of hypothesized - may offer useful insights. By combining two datasets, we exploit the variability in SP data for estimating RP model parameters; in this manner we improve on the accuracy of parameter estimates while exploiting the advantages of both datasets. In general, the realization that RP and SP
methods have both advantages and limitations has led researchers to the development of techniques for combining these data in joint analyses (Dissanayake and Morikawa, 2001; Dissanayake, 2001; Dissanayake and Morikawa, 2000; Morikawa, 1989, Ben-Akiva and Morikawa, 1990; Polydoropoulou and Ben-Akiva, 2001). Comparing utility model parameters from different data sources has been the subject of considerable research (Louviere, Hensher and Swait, 2000). Comparing utility model parameters from different data sources has been the subject of considerable research (Louviere, Hensher and Swait, 2000).

RP data are naturally constrained in terms of being able to collect information on the non-chosen alternatives; to this end, our analysis requires an approach for collecting data outside the existing ranges. This is covered by the collection of SP data. At the same time, SP data are particularly useful when RP data do not have sufficient variation in attributes or too much correlation among the attributes (Mabit, 2010). This study explores altered travel patterns during subway closures by investigating the reaction of three categories of travelers:

1. Travelers who remain on the partly disrupted network during the disruption. These travelers use the parts of the line that remain in operation along with the alternative means provided by the operator for the disrupted parts,
2. Travelers who during closure shift to alternative modes and return to the metro system after the line has been restored, and
3. Travelers who adopt an alternative mode and do not return to PT even after restoration.

For this analysis we need both Revealed and Stated Preference techniques to explore the importance of trip and traveler characteristics (i.e. travel time, cost, previous experience, and so on) on travel pattern selection during closure.

Polydoropoulou and Ben-Akiva (2001) described the benefits of using a combined RP/SP Nested Logit model for considering access and main mode choice for new mass transit project in Tel-Aviv metropolitan area. Sobel (1980) used various types of NL structures to examine travel demand forecasting for individuals. Talvitie (1978) estimated commuting-based mode choices by using two-level NL model and keeping the upperlevel for line haul choices and the lower-level for access or egress modes, and extended the analysis considering income and work trip sub-groups (Talvitie, 1978). Mannering et
al. (1994) developed a NL model to investigate individual travel behavior, emphasizing mainly on activity type and activity chaining aspects, where the upper-level represents the activity type choice and the lower-level shows the number of stops in the activity chain. Train \& Wilson (2007) developed a model that included unobserved influence of the RP choice on the SP choice experiment. The authors developed their model for both SP-offRP and pivoted SP experiments. Their results showed that there is some effect in some of the specifications that they investigated. Hensher, Rose and Greene (2005) advise practitioners to combine RP and SP sources and clarify that the respondents sampled for each data source need not be the same. The authors strongly support the collection and use of RP data to provide information on the likely attribute levels experienced within markets from which SP experimental design attribute levels can be pivoted.

In this chapter the choice of mode during a subway closure is modeled as a Nested Logit model. A two-level NL model with one branch including all the RP alternatives and dummy branches for the SP alternatives is developed since this is the most common practice when pooling RP and SP data sources.

### 7.2 Combining RP-SP data in Travel Behavior Modeling

The preceding discussion provides a basis to address the general problem of combining RP and SP data. The mode choice situation that is considered in this research is a wellknown Multinomial Logit model (MNL) of the following form:

$$
P_{n}(i)=\frac{e^{V_{i n}}}{\sum_{j=1}^{I} e^{V_{j n}}}, \quad j=1, \ldots ., i, \ldots, I \in C_{n} \forall i \neq j
$$

Where, $P_{n}(i)=$ probability of traveler $n$ choosing alternative $i$
$V_{i n}=$ is a determinist component of utility of a function of exogenous variables and it can be written as
$V_{i n}=a_{i}+\beta X_{\text {in }}$

Where $a_{i}=$ constant specific to alternative $i$
$\beta$ is a vector of parameters to be estimated
$X_{i n}$ is vector of attributes for the individual $n$ and the alternative $i$.

The random error $\varepsilon$ term is associated with the independent variables and is assumed to be the same for estimation and prediction cases in case of using RP data. In case of using SP data though, the utility computed is pseudo utility and the random error term (n) associated is a difference between random error terms of RP and SP data, and hence cannon be used for prediction purposes.

To improve on the reliability of parameter estimates the model is developed as a combined RP/SP case. At first, the RP and SP models are developed separately and then the two models are combined; the final sample comprises of 2982 choice occasions (1038 RP respondents and 1944 SP respondents).

There are several factors that influence travelers when deciding which mode to use during a metro closure; these include mode features (such as the cost, frequency, invehicle travel time, waiting time and walking distance, parking search time etc), as well as the connection of the subway network within the city transport system. The utility functions for the RP and SP data are presented below:

## Revealed Preference

$U_{i}^{R P}=A S C_{i}^{R P}+\beta_{\text {cost }}^{R P} * \operatorname{cost}_{i}^{R P}+\beta_{\text {transfer }}^{R P} *$ transfer $_{i}^{R P}+\beta_{\text {ttime }}^{R P} * t t i m e ~ i e r ~ \beta_{\text {work }}^{R P} *$ $\operatorname{work}_{i}^{R P}+\varepsilon_{\imath}^{R P} \quad \forall i \in C^{R P}$

## Stated Preference

$$
\begin{aligned}
& U_{j}^{S P}=A S C_{j}^{S P}+\beta_{\text {cost }}^{S P} * \text { cost }_{j}^{S P}+\beta_{\text {transfer }}^{S P} * \text { transfer }_{j}^{S P}+\beta_{\text {invt }}^{S P} * \text { invt }_{j}^{S P}+\beta_{\text {ovt }}^{S P} * \\
& \text { ovt }{ }_{j}^{S P}+\beta_{\text {work }}^{S P} * \text { work }_{j}^{S P}+\beta_{\text {flex }}^{S P} * \text { flex }_{j}^{S P}+\beta_{\text {agegr } 1}^{S P} * \operatorname{agegr} 1_{j}^{S P}+\beta_{\text {agegr } 2}^{S P} * \\
& \text { agegr2 } j_{j}^{S P}+\beta_{\text {agegr3 } 3}^{S P} * \operatorname{agegr} 3_{j}^{S P}+\beta_{\text {male }}^{S P} * \operatorname{male}_{j}^{S P}+\beta_{L_{-} I N C}^{S P} * L_{-} I N C_{j}^{S P}+\beta_{H_{-} I N C}^{S P} * \\
& H_{-} I N C_{j}^{S P}+\varepsilon_{j}^{S P} \forall j \in C^{S P}
\end{aligned}
$$

Where $i, j$ is an alternative in choice sets $C^{R P}, C^{S P}$ respectively, $C^{R P}=\{i, i=1$ bus, 2 car, 3, taxi, 4 metro $\}, C^{S P}=\{j, j=1$ bus, 2 car, 3, taxi, $\}$ and
$\operatorname{cost}_{i}^{R P}$, transfer ${ }_{i}^{R P}$, ttime $_{i}^{R P}$, work $_{i}^{R P} ; \operatorname{cost}_{j}^{S P}$, transfer ${ }_{j}^{S P}$, invt $_{j}^{S P}$, work ${ }_{j}^{S P}$, flex $_{j}^{S P}$, agegr $1_{j}^{S P}$, agegr2 $2_{j}^{S P}$, agegr $3_{j}^{S P}$, male $j_{j}^{S P}, L_{-} I N C_{j}^{S P}, H_{-} I N C_{j}^{S P}$ are the explanatory variables for RP and SP described as follows:

- $\operatorname{cost}_{i}^{R P}$ is the travel cost of the trip referring either to transit fare or taxi cost or generalized car travel cost in euros; the average calculated transit fare during the
closure was 0.46 for a 90 minute trip on all public transport modes ${ }^{1}$. During the 5-month closure the travel card holders of metro network were allowed to travel for free on the bus-bridge line and on all bus lines.
- $t_{\text {time }}^{i}{ }_{i}^{R P}$ is the door-to-door travel time for mode $i$ in minutes,
- transfer ${ }_{i}^{R P}$ is the transfer inconvenience expressed as the number of transfers within the described trip during the closure,
- $\operatorname{work}_{i}^{R P}$ is a dummy variable which is 1 if the purpose of the described trip during the closure is work and 0 otherwise.

The explanatory variables of the SP survey are described as follows:

- $\operatorname{invt}_{j}^{S P}$ is the in-vehicle travel time for mode $i$ in minutes,
- $o v t_{j}^{S P}$ is the out-of-vehicle travel time for mode $i$ in minutes
- $\operatorname{cost}_{j}^{S P}$ is the travel cost of the trip referring either to transit fare or taxi cost or car generalized travel cost in euros
- transfer ${ }_{j}^{S P}$ is the transfer inconvenience expressed as the number of transfers within the described trip during the closure,
- $\operatorname{work}_{j}^{S P}$ is a dummy variable which is 1 if the purpose of the described trip during the closure is work and 0 otherwise
- $f l e x_{j}^{S P}$ is a dummy variable which is 1 if the respondent works fixed hours, and 0 if works flexible hours or hours which are variable according to the requirements of the job
- agreg1 $1_{j}^{S P}$ is a dummy variable which is 1 if the respondent is $18-35$ years old and 0 otherwise
- $\operatorname{agreg} 2_{j}^{S P}$ is a dummy variable which is 1 if the respondent is $35-45$ years old and 0 otherwise
- agreg3 $3_{j}^{S P}$ is a dummy variable which is 1 if the respondent is $45-55$ years old and 0 otherwise

[^16]- agreg $4_{j}^{S P}$ is a dummy variable which is 1 if the respondent is $>55$ years old and 0 otherwise
- $L_{-} I N C_{j}^{S P}$ is a dummy variable which is 1 if the respondent earns less than 800 euros per month and 0 otherwise
- $H_{-} I N C_{j}^{S P}$ is a dummy variable which is 1 if the respondent earns more than 1500 euros per month and 0 otherwise

Based on the RP and Logit model, we can get the probability of alternative i chosen by traveler n that is:
$P_{i n}^{R P}(i)=\frac{e^{V_{i n}^{R P}}}{\sum_{i=1}^{I} e^{V_{i n}^{R P}}}$
Where $V_{i n}^{R P}$ is the observed part of the RP utility.
Then, the log likelihood of RP data is given by:
$\ln L^{R P}\left(\widehat{A S} C_{i}^{R P}, \widehat{\beta}\right)=\sum_{n \in R P} \sum_{i \in C_{n}^{R P}} y_{(R P) i n} \ln p_{i n}^{R P}$
Where, $y_{(R P) \text { in }}=1$ if traveler $n$ chooses alternative $i$, and $=0$ otherwise.
The joint RP-SP model assumes that the tradeoff relationship among major attributes is common to both RP and SP; this is reflected in the utility functions which give the same attributes common parameters $\left(\beta_{\text {cost }}^{R P}=\beta_{\text {cost }}^{S P}=\beta\right.$ as an example $)$.

## Discussion on the Estimated Coefficients

The model estimation results for the separate SP modes is slightly distinct from those models calibrated previously for all sets of variables.

In the joint RP-SP, generic attributes were used for each level-of-service variable since the preliminary modeling results done using specific attributes were unsatisfactory. This indicates that travelers perceived cost, travel time and transfer inconvenience uniformly, irrespective of the traveling mode.

### 7.3 Econometric Analysis

As explained above, it is feasible to combine the two discrete-choice models employed in this dissertation since they reflect the same process of selecting an alternative mode of
travel during Metro disruptions. Both are applications of random utility theory. Each selection model considers three common attributes: travel cost, travel time, transfer inconvenience. Since its model is based on random utility theory and can be estimated with the Nested Logit Model, each can be used for analyzing travel behavior during Metro disruptions. The results of each approach taken alone and the combined approach can be compared in the end of the analysis.

### 7.4 The Survey and Data Analysis

The dataset for the study is a joint RP and SP dataset. The RP data comes from data collected just after Metro Line 1 was back in operation after a 5 -month closure for upgrade works. The SP data is based on an internet survey that was developed to collect additional data to model the travel behavior responses of metro travelers to changes in travel conditions, including travel times, transit fares, fuel cost, transit service frequency and transfer inconvenience, during a hypothetical 24hr closure of the Metro/Tram and Suburban Railway Network. Thus the final sample comprises of 2982 choice occasions (1038 RP respondents and 1944 SP respondents).

## Revealed Preference Model Choice of Alternative Mode Model during Metro Disruptions

We develop a choice of alternative mode of travel during Metro Disruptions. The alternative modes are differentiated for each survey type. Considered available alternative modes during the 5-month partial closure of Metro Line 1 are Bus, Metro (the operating part of the network), Tram, Private Car, Taxi, Bike, Motorcycle. Based on the choice of mode of the respondents of the survey we identified the main mode of travel of each traveler. We also omitted from the dataset the responses where the main mode of journey was either walk or bike, as the only available information was travel time. The utility of each alternative mode $i$, is represented by $V_{i}$. The alternative specific constants $A S C_{i}$, are included for each alternative mode in the RP dataset except for one of them which is normalized to 0 for identification purposes.

The RP data does not include any information on the travel time of the non-chosen alternatives, and hence assumptions based on the average travel time of each mode have been made, based on the origin-destination of each trip, the time of the day that it took place, assumptions of travel speeds in am peak and off-peak hours in Athens. Since, there was no data available for the non chosen alternatives in the RP survey, the authors developed estimations of travel time and travel costs using supplementary data sources.

The fuel price was estimated at 1.64 euros/lt (2010 price), the average fuel consumption was estimated at $0.09 \mathrm{lt} / \mathrm{km}$ in Athens city centre. Fuel consumption is assumed to account for the $75 \%$ of the operating cost of a trip in Athens city centre (See Chapter 6 for details). For taxis the estimation of travel cost was calculated as follows for the base trip category; commuting. For taxis, tariff is 0.18 euros $/ \mathrm{min}$ and value of time for commuters traveling by taxi is calculated to be 6.62 euros $/ \mathrm{hr}$.

The lack of variability in some attributes in RP surveys, precludes a statistically significant estimation of key parameters of the choice models (Atasoy, Bierlaire, 2012). The SP data is used to overcome this issue of limited variability within the RP data. The SP data comes from an internet survey which was described in detail in Chapter 5. The respondents were presented with hypothetical choice of mode situations and offered three alternatives during a 24 hr closure of all Subway Network among car, bus and taxi. The explanatory variables of the SP survey are described as follows:

## Stated Preference Model Choice of Alternative Mode Model during Metro Disruptions

The SP model is also a logit model. The choice set consists of three alternatives. The SP data consists of two groups of travelers; car owners and car non-owners. The utility of each alternative mode $i$, is represented by $V_{i}$. Similar to the RP model, the parameters of the price and transfer inconvenience are constrained to be the same as the price and transfer parameters of the RP model presented in Section 7.2. Similarly the parameter of trip purpose is also designed to be the same as the parameter of the RP model.

In the SP model, there are additional sociodemographic variables since it is based on a rich dataset. For all metro travelers we have the information of working schedule flexibility. A study of choice of mode of commuters from North Kent (Wardman, 1988), found that those travelers working variable hours were found to have the highest values of time, presumably reflecting the longer hours worked and thus the greater constraints upon available time.

In this section the RP model is estimated with the SP model to take advantage of its elasticity. Since the models for RP and SP datasets are estimated simultaneously, we need to define a scale variable, scale $e_{\text {sp }}$. The scale of the RP data is fixed to 1 and scale $_{e p p}$ is to be estimated to capture differences in the covariance structure of the error terms of the two models.

The universal choice set includes 7 alternatives: RP; main mode car, main mode bus, main mode taxi, main mode metro (by this we refer to the operating part of the line during the 5 -month closure), SP ; car, bus and taxi.

For the population represented by the sample, indirect utility from trip characteristics takes the form:

$$
\begin{aligned}
& V_{\text {in }}^{R P}=A S C_{i}^{R P}+\beta_{\text {cost }}^{R P} * \operatorname{cost}_{i}^{R P}+\beta_{\text {transfer }}^{R P} * \text { transfer }_{i}^{R P}+\beta_{\text {ttime }}^{R P} * \text { ttime }_{i}^{R P}+\beta_{\text {work }}^{R P} * \\
& \text { work }_{i}^{R P} \forall i \in C^{R P}
\end{aligned}
$$

which is a function of $\beta$, the vector of coefficients associated with the vector of attributes describing trip related characteristics. The regression is estimated with a Multinomial Logit model using Maximum Likelihood Estimation (MLE) techniques. The MNL model has the Independence of Irrelevant Alternatives (IIA) property. Table 7-2 gives the estimates for the 'best' MNL model using actual travel data related to the choice of alternative during the 5 -month closure of the metro line.

Table 7-1 Separate MNL model of RP survey data

| Attribute | Parameter | t-value |
| :--- | :--- | :--- |
| ASC BUS | -1.341 | -2.983 |
| ASC CAR | -0.741 | -3.295 |
| ASC METRO | -2.823 | -6.104 |
| TTIME | 0.001 | $\mathrm{n} / \mathrm{s}$ |
| TRANSFER | 1.599 | 5.045 |
| COST | -0.787 | -7.975 |
| Work Dummy for metro | -0.846 | -4.088 |
| Sample Size (observations) | 1038 |  |
| Rho-Square | Not computed |  |
| Log-Likelihood | -903.6155 |  |

According to this model, respondent travel time is not statistically significant. The lack of variability in some attributes in RP surveys precludes a statistically significant estimation of key parameters in choice models (22). SP data are used to overcome the issue of limited variability within RP data. The parameters for the dummy variable of trip purpose for work were removed from the model for bus and car users since they 'weakened' the relations of the other variables. Overall, the results of the RP model are highly significant except for travel time. Lack of significance may also be - at least in part - attributed to the assumption regarding travel times for the non-chosen alternatives.

### 7.5 Stated Preference Model

Tables 7-2 and 7-3 give the best MNL model estimates using the SP data described, for car owners and car non-owners respectively related to altered travel patterns during a 24 hr hypothetical closure of subway Network. The coefficients fall into three categories: 1) coefficients that are uniquely determined by either the RP or the SP data, 2) coefficients that are common in the two data sets (except for a scale effect) and 3) coefficients that are different in the two data sets.

For the population represented by the sample, indirect utility from trip characteristics takes the form
$V_{j}^{S P}=A S C_{j}^{S P}+\beta_{\text {cost }}^{S P} * \operatorname{cost}_{j}^{S P}+\beta_{\text {transfer }}^{S P} *$ transfer $_{j}^{S P}+\beta_{\text {invt }}^{S P} * i n v t_{j}^{S P}+\beta_{\text {ovt }}^{S P} * o v t_{j}^{S P}+$ $\beta_{\text {work }}^{S P} *$ work $_{j}^{S P}+\beta_{\text {flex }}^{S P} * f l e x_{j}^{S P}+\beta_{\text {agegr } 1}^{S P} *$ agegr $1_{j}^{S P}+\beta_{\text {agegr } 2}^{S P} *$ agegr2 $2_{j}^{S P}+\beta_{\text {agegr } 3}^{S P} *$ agegr3 $j_{j}^{S P}+\beta_{\text {male }}^{S P} *$ male $_{j}^{S P}+\beta_{L_{-} I N C}^{S P} * L_{-} I N C_{j}^{S P}+\beta_{H_{-} I N C}^{S P} * H_{-} I N C_{j}^{S P} \forall j \in C^{S P}$

Table 7-2 Stated Preference Model-Car owners

| Variable | SP-Sample MNL |  |
| :--- | :--- | :--- | :--- |
|  | Param. | t-value. |
| Constants |  |  |
| SP Sample |  |  |
| BUS | 1.033 | 11.238 |
| CAR | 1.596 | 19.173 |
| Taxi (reference base) |  |  |
| Level of Service Variables | -0.039 | -25.025 |
| In-vehicle travel time (in mins) (SP) | -0.040 | -9.271 |
| Out-of-vehicle travel time (mins) (SP) | -0.241 | -7.781 |
| Transfer inconvenience (RP,SP) | -0.212 | -25.330 |
| Cost (RP,SP) |  |  |
| Socio Demographic Variables |  |  |
| Low_Income (<800) | 0.309 | 4.660 |
| For bus users |  |  |
| High_Income ( $>1500$ ) | -0.338 | -4.774 |
| For bus users |  |  |
| Age |  |  |
| Age 35-45 | -0.069 | -0.967 |
| For bus users |  |  |
| Trip purpose work | -0.183 | -2.941 |
| For car users |  |  |
| Gender Male | 0.213 | 4.125 |
| For Car Users |  |  |
| Work schedule flexibility | -0.134 | -2.552 |
| For Car users | -6708.093 |  |
| Log likelihood | -7829.098 |  |
| Null Log Likelihood | 0.143 |  |
| Rho Square |  |  |

Table 7-3 Stated Preference Model-Car non-owners

| Variable | SP-Sample MNL |  |
| :---: | :---: | :---: |
|  | Param. | t-value. |
| Constants |  |  |
| SP Sample |  |  |
| BUS | -0.298 | -3.433 |
| Taxi (reference base) |  |  |
| Level of Service Variables |  |  |
| In-vehicle travel time (in mins) (SP) | -0.038 | -21.005 |
| Out-of-vehicle travel time (mins) (SP) | -0.028 | -4.871 |
| Transfer inconvenience (SP) | -0.185 | -6.060 |
| Cost (SP) | -0.299 | -37.866 |
| Socio Demographic Variables |  |  |
| Low_Income (<800) |  |  |
| For bus users | 0.535 | 8.486 |
| High_Income ( $>1500$ ) |  |  |
| For bus users | -0.436 | -3.241 |
| Age |  |  |
| Age 35-45 |  |  |
| For bus users | 0.003 | 0.028 |
| Trip purpose work |  |  |
| For car users |  |  |
| Gender Male |  |  |
| For bus Users | 0.380 | 7.415 |
| Work schedule flexibility |  |  |
| For bus users | -0.029 | -. 590 |
| Sample size (observations) |  |  |
| Log likelihood |  |  |
| Null Log Likelihood |  |  |
| Rho Square |  |  |

## Combined RP/SP Model for Estimating Alternative Mode Choice during Metro Disruptions

Given that the attributes and variables contained within the RP data sets are likely to be ill conditioned(due to multicollinearity, little or no variation in the attribute levels, etc), parameter estimates obtained from RP data are likely to be biased (Hensher, Rose and Greene, 2005). In our case, where the Metro alternative is present within the RP component but not within the SP , we use the RP data to obtain the preference function for that alternative. Hensher et al. (2005) note that the sample of respondents for the joint RP-SP set need not be the same. In the joint RP/SP, generic attributes were used for each level-of-service variable since the preliminary modeling results using specific attributes were not satisfactory. This suggests that travelers perceive cost, travel time, and transfer inconvenience uniformly, irrespective of the traveling mode.

The combined model shares some of the coefficients particularly for common attributes belonging to RP and SP models. Since the models for the RP and SP datasets are estimated simultaneously, we need to define a scale variable, scale ${ }_{\mathrm{sp}}$. The scale for the RP data is fixed to 1 and scale $_{\text {sp }}$ is to be estimated to capture differences in the covariance structure of the error terms in the two models. The coefficients fall into three categories: 1) coefficients that are uniquely determined by either the RP or the SP data, 2) coefficients that are common for the two data sets (except for a scale effect), and 3) coefficients that are different in the two data sets.

The universal choice set includes 9 alternatives; for RP: car, bus, taxi, metro; for SP: car, bus and taxi (for car owners/CO) and bus, taxi (for car non-owners/NCO). The model is primarily estimated with a Multinomial Logit model and a using Maximum Likelihood Estimation (MLE) techniques.

Initial results confirm that for travelers who own a private vehicle the alternative specific constant for car is positive and higher than the one for bus; this indicates that all else being equal, car is the most preferable choice. Negative signs for time, cost and number of extra transfers within a journey indicate that an increase in travel time, cost, or number of transfers will reduce the utility (and thus the chosen probability) of an alternative.

The 'number of transfers' variable both for car and car non-owners is negative and statistically significant. The ratio of transfer over cost is higher for car owners (1.14) compared to the ratio of transfer over cost for car non-owners (0.62), which implies that car owners place a higher implied monetary value on each transfer than car non-owners do. The high value of the existing transfer penalty expresses the need for:

1. an increased direct connectivity of the PT network and the road network to reduce transfer rate
2. improving the quality of transit transfers, by working on time schedule, on-time arrival, and transfer fare
3. enhancing safety of transfer and activity consolidation through intermodal transfer stations offering opportunities for productive time use (e.g. post/bank counters, restaurants, wifi zones within metro/bus stations), thus decreasing transfer disutility.
4. Improve the physical aspects of transfer facilities (such as distance to make a transfer, lighting, seating, signage, protection from weather)

According to previous studies on transfer facilities, a transfer accounts for approximately one quarter of total generalized costs (or time), which means that the shorter the trip the more significant the impact of transfer ${ }^{1}$.

The utility is generally unitless. Assuming that the travel cost is measured in euros and the travel time is measured in minutes, the ratio of the coefficient for the travel time over the coefficient for the travel cost would have units of euros/min (or if multiplied by 60 euros $/ \mathrm{hr}$ ), which is the expected unit for VOT measure (equation 3).

VOT $=\left(\frac{\beta_{\text {in-vehtime }}}{\beta_{\text {cost }}}\right) * 60$

The estimated VOT (in-vehicle time/travel cost) from the SP only model for car owners is higher ( 11.04 euros $/ \mathrm{hr}$ ) than car non-owners ( 7.63 euros $/ \mathrm{hr}$ ) which implies that car owners place a higher implied monetary value on each additional minute of travel than car non-owners do. There is evidence that in-vehicle travel time is almost equally important for car owners (VOT of 11.04 euros $/ \mathrm{hr}$ ) to out-of vehicle travel time (wait, walk) ( 11.32 euros $/ \mathrm{hr}$ ) due perhaps to favourable weather conditions in Attika Region, as waiting/walking time is perceived especially burdensome when they have to wait in difficult environments, such as in cold, hot or rainy weather or in seemingly unsafe or insecure condition. The opposite holds for car non-owners, where in-vehicle travel time is perceived particularly onerous (VOT of 7.63 euros $/ \mathrm{hr}$ ) compared to out-of-vehicle travel time ( 5.62 euros $/ \mathrm{hr}$ ), , which shows that car non-owners are more sensitive to out-of-vehicle time which is rather controversial with what most studies support. However, we might argue that travel behavior and perception of travel time is very different under different circumstances (during and before/after disruptions). A travelers' in-vehicle travel time can be more onerous than his actual waiting/walking time during metro disruptions. This might be partly explained by the difference in perceived and actual time particularly on walking and waiting time. This difference can vary by conditions such as headways, reliability, safety security, comfort, convenience, and conditions where travelers are forced to wait due to operational disruptions.

[^17]
### 7.6 Theoretical Framework-The Nested Logit Model

As demonstrated in Chapter 3, the Multinomial Logit model has a simple and closedform mathematical structure; however, it is saddled with the IIA restriction at the individual level. One of the three types of discrete choice models that relaxes the IIA assumption is the NL model. In the following paragraphs only a small introduction of the NL model is provided, which is most relevant to the present study. The NL model allows for partial relaxation of the assumption of Independence from Irrelevant Alternatives (IIA) among random components; it hence allows for correlation among alternatives. By rejecting the IIA hypothesis, we have alternatives whose utility functions are correlated in their error terms. Nested logit models and Multinomial Probit models are used when there are shared unobserved components associated with different choices or alternatives (Bhat, 1998). In these cases the utilities of the elements of the corresponding multidimensional choice set cannot be independent.Hence, the NL model is considered to perform the analysis. MNP models are rejected due to their complexity function of the likelihood function to estimate more than 4 or 5 alternatives.

In our survey we have two sets of attributes, observed and unobserved, associated with each alternative to the choice outcome. By linking the two data sets, individuals act as if they are maximizing utility. The solution to the maximization problem is an indirect utility expression for each alternative which is a function of the observed and the unobserved attributes of alternatives. The observed levels of the attributes of alternatives typically obtained in an RP study are sought directly from the traveler. Within the SP study though, the attribute levels are fixed by the researcher. While the choice outcome in the RP survey is known, in the SP survey the potential outcome is not, and comes from maximizing the likelihood of occurrence given the combination of attribute levels in the experiment. Though SP experiments involve variation of attribute levels in the experimental design, each traveler is exposed to different combination of values for the rest of the explanatory variables. This is called the unobserved heterogeneity effect (Bhat, 1995). Bhat (1995) supports the use of questions related to actual past choices, habits and inertia on actual current choices of the SP experiment (this is called stated dependence). He also believes that there is no reason to assume that the variance of the unobserved factors in the RP set will be the same with the variance of the unobserved factors in the SP setting (scale difference). These issues need to be considered when combining RP/SP datasets.

We propose a nested structure where RP alternatives are placed under a RP nest and each SP alternative is placed in a single alternative nest with a scale parameter $\mu$, where $\mu$ is the factor that scales the SP error of each alternative with respect to the RP error. The general approach of Nested multinomial is introduced in Heiss (2002).To scale the variances of the unobserved effects in the SP component relative to the RP component we use Full-Information Maximum Likelihood (FIML). After testing different substitution patterns between the SP options or between car owners and car non-owners in the SP data set, we did not find any evidence of correlation among the SP modes.

Figure 7-1 shows the artificial tree structure in our RP/SP model, where $\mu_{\mathrm{i}}(\mathrm{i}=1,2,3,4$, 5) is the scale parameter for each SP alternative ( $i$ ). The SP task has three travel options: car (which includes drivers and passengers), taxi and bus for travelers who own a car and two: taxi and bus for travelers who do not own a car.

The SP task has three travel options: Drive alone or Ride Share, Taxi or Bus. Drive alone/ Ride Share and taxi options are described by 4 attributes (total in-vehicle travel time, total out-of-vehicle travel time and cost) while bus option is described by 4 attributes (total in-vehicle travel time, total out-of-vehicle travel time and fare). All attributes were assigned three levels and a choice experiment was designed by treating all attributes as a fractional factorial orthogonal design (detailed description in Chapter 6).


Figure 7-1 The Nested Structure Used in model Estimation
Bradley and Daly (1992) have suggested a scaling approach which correlates the variance of error term of different observations. The difference between the RP and SP errors can be represented as a function of their variances such that:
$\mu^{2}=\operatorname{var}\left(\varepsilon_{i}^{R P}\right) / \operatorname{var}\left(\varepsilon_{j}^{S P}\right)$

Where $\mu$ is the scale factor, scaling the error in SP with respect to the error in RP. Based on the above theoretical framework the utility functions in case of combination of RP and SP data can be written for an alternative $i \in A$ (Ben Akiva and Morikawa, 1990), as:
$U_{i}^{R P}=a X_{i}^{R P}+\beta Y_{i}^{R P}+\varepsilon_{i}$
$\mu U_{j}^{R P}=\mu\left(a X_{j}^{R P}+\gamma Z_{j}^{R P}+\varepsilon_{j}\right)$
Where $\alpha, \beta$ and $\gamma$ are parameters to be estimated; $X^{R P}$ and $X^{S P}$ are vectors of common attributes to both type of data and $Y^{R P}$ and $Z^{S P}$ are the vectors of attributes specific to SP or RP data respectively. The stochastic errors $\varepsilon_{i}$ and $\varepsilon_{j}$ are independently distributed Gumbel with zero mean the choice probabilities are defined on the basis of their utility functions on a logit type structure. The maximization of the joint likelihood function is a non linear problem because $\mu$ multiplies some of the parameters to be estimated. To solve this problem two techniques have been used with good results: the simultaneous estimation method developed by Bradly and Daly (1991) and the sequential estimation method proposed by Ben-Akiva and Morikawa (1990).

The probability of the alternative $i$ chosen by traveler $n$ in RP data is:
$P_{i n}^{R P}(i)=\frac{e^{V_{i n}^{R P}}}{\sum_{i=1}^{4} e^{v_{i n}^{R P}}}$
The probability of the alternative $i$ chosen by traveler $n$ in SP data is:
$P_{j n}^{S P}(i)=\frac{e^{\mu V_{j n}^{S P}}}{\sum_{j=1}^{3} e^{\mu V_{j n}^{S P}}}$
Where $V^{R P}, V^{S P}$ is respectively the observed part of the RP and SP utility.
The log likelihood of the combined data is the sum of the multinomial log likelihood of the RP and SP data. The scale factor $\mu$ plays a crucial role in the process of combining data. To scale the variances of the unobserved effects in the SP component relative to the RP component we use the most efficient approach (Hensher and Bradley, 1993) which uses the method of full-information maximum likelihood (FIML).

### 7.7 Joint RP-SP Model Results

A number of different model structures were estimated in the analysis. Table 7-4 provides the results of the joint RP-SP models. The first model is the "RP-SP MNL" model with RU1 form, the second is the "RP-SP MNL" model with RU2 form, and the third is a joint "RP-SP MNL" model with normalized RP, SP to 1 and RU2 form.

The combined model shares some of the coefficients especially for common attributes belonging to RP and SP models. In particular, the following assumptions have been considered in this model:

- Level of service variables such as travel cost, transfer inconvenience share for all RP and SP based utilities in the combined model.
- Level of service variables such as in-vehicle time, out of vehicle time share for all SP based utilities in the combined model
- Mode specific dummies for all modes are specified separately for each alternative mode in the RP (work purpose) and the SP utilities (age group dummies, work purpose, working schedule flexibility, income dummies, gender)
- A scale parameter is included for each alternative mode in the SP utility functions to observe the relative level of randomness in RP and SP data sources.

Simultaneous estimation (full information maximum likelihood) method is used to estimate the combined RP/SP Nested Logit model. Basically it is assumed that the scale parameter for the bottom level (level of mode choices) is equal to one and then, the scale parameter for the upper level is estimated. Attributes, which are obtained from the RP and SP databases, are explicitly incorporated for the analysis.

Table 7-4 provides the results of the combined RP/SP models as estimated with a MNL model and a NL model. The combined model shares some of the coefficients particularly for the common attributes belonging to the RP and SP models.

TABLE 7-4 Joint Choice of Mode Nested Model for Travelers during Metro Disruptions

| Variable | $\begin{gathered} \hline \text { Joint RP-SP } \\ \text { MNL } \end{gathered}$ |  | Joint RP-SP NL <br> RU1 FORM |  |
| :---: | :---: | :---: | :---: | :---: |
|  | Param. | t-value | Param. | t-value |
| Constants |  |  |  |  |
| Car (RP) | 0.432 | 2.727 | 1.150 | 1.986 |
| Bus (RP) | 1.455 | 10.976 | 1.450 | 10.826 |
| Taxi (RP) | 0.180 | $1.005^{\mathrm{n} / \mathrm{s}}$ | 1.140 | $1.355^{\mathrm{n} / \mathrm{s}}$ |
| Car (SP) | 1.540 | 18.167 | 1.839 | 2.434 |
| Bus (SP-CO) | 0.722 | 7.146 | 1.377 | 2.237 |
| Bus (SP-NCO) | 0.209 | 2.319 | 0.496 | 1.319 |
| Taxi (base mode for SP) |  |  |  |  |
| Metro (base mode for RP) |  |  |  |  |
| Level of Service Variables |  |  |  |  |
| Door-to-door Travel Time (in mins.) (RP) | -0.002 | $-0.521^{\mathrm{n} / \mathrm{s}}$ | -0.000 | $-0.086^{\mathrm{n} / \mathrm{s}}$ |
| In-vehicle travel time (in mins) (SP) | -0.038 | -32.081 | -0.075 | -2.464 |
| Out-of-vehicle travel time (mins) (SP) | -0.036 | -9.450 | -0.078 | -2.466 |
| Transfer inconvenience (RP,SP) | -0.183 | -8.643 | -0.314 | -3.264 |
| Cost (RP,SP) | -0.262 | -45.778 | -0.505 | -2.410 |
| Socio Demographic Variables |  |  |  |  |
| Low_Income (<800) (SP) |  |  |  |  |
| For bus users (CO) | 0.326 | 4.309 | 0.555 | 2.325 |
| For bus users (NCO) | 0.512 | $0.069^{\text {n/s }}$ | 0.496 | $1.319^{\mathrm{n} / \mathrm{s}}$ |
| High_Income ( $>1500$ ) |  |  |  |  |
| For car users (SP) | 0.231 | 3.287 | 0.494 | 2.128 |
| Age 35-45 (SP) |  |  |  |  |
| For bus users - CO | -0.092 | $-1.235^{\text {n/s }}$ | -0.142 | $-1.002^{\mathrm{n} / \mathrm{s}}$ |
| For bus users - NCO | 0.023 | $0.246^{\mathrm{n} / \mathrm{s}}$ | 0.042 | $0.246^{\mathrm{n} / \mathrm{s}}$ |
| Trip purpose work |  |  |  |  |
| For bus users- CO (RP,SP) | -0.148 | -1.677 | -0.239 | -1.556 |
| For car users (RP,SP) | -0.295 | -3.766 | -0.536 | -3.021 |
| For bus users-NCO (SP) | -0.078 | $-1.208^{\text {n/s }}$ | -0.144 | $-1.119^{\mathrm{n} / \mathrm{s}}$ |
| For metro users (RP,SP) | -1.019 | -4.621 | -1.124 | -4.467 |
| Gender Male |  |  |  |  |
| For car Users (SP) | 0.214 | 3.981 | 0.502 | 2.065 |
| Work schedule flexibility (SP) |  |  |  |  |
| For Car users | -0.134 | -2.469 | -0.277 | -1.801 |
| IV Parameters |  |  |  |  |
| RP |  |  | 1.000 | Fixed parameter |
| Bus-SP |  |  | 0.557 | 2.475 |
| Car-SP |  |  | 0.419 | 2.457 |
| Taxi-SP |  |  | 0.559 | 2.416 |
| Bus (car non-owners)-SP |  |  | 0.578 | 2.501 |
| Taxi (car non-owners)-SP |  |  | 0.570 | 2.417 |
| Number of observations | 18534 |  | 18534 |  |
| Log likelihood at convergence | -12624.40 |  | -12586.14 |  |
| Log likelihood constants only | -14897.30 |  | -34647.44 |  |
| Likelihood Ratio | 599.66 |  | 44122.60 |  |
| Probability> chi-square value | 0.000 |  | 0.000 |  |
| Rho-square | 0.410 |  | 0.637 |  |

${ }^{\mathrm{n} / \mathrm{s}}$ not significant at $10 \%$ significance level

Table 7-4 shows the parameters for the combined RP/SP Nested Logit model. Most of the parameters are statistically significant with expected signs and adequately describe choice of alternative modes selected during metro disruptions. The Nested Model is a statistically significant improvement to the base MNL model $(2 L L=(-12624.40-$ $(-12586.14)) \cong 76>X_{0.05,5 d f}^{2}=11.07$ (for 0.05 significance level and 5 degrees of freedom), and we hence reject null hypothesis that MNL is better. Mode specific dummies have been introduced for each traveler to observe their individual intention for travel alternatives in the system. Results of the NL model for the mode specific dummies indicate that the use of bus $(\mathrm{RP}=1.450, \mathrm{SP} / \mathrm{CO}=1.377, \mathrm{SP} / \mathrm{NCO}=0.496)$, car (1.150), and taxi (1.140) is attractive for travelers; parameters are positive and statistically significant.

Coefficients for in-vehicle travel time, out-of vehicle travel time, cost, and transfer inconvenience of the NL model are negative (and statistically significant). The joint RPSP analysis with the MNL model confirms the initial findings from the SP only model that travelers almost equally value in-vehicle travel time with out-of vehicle travel time. However, the joint RP/SP NL model analysis produced a higher absolute value for the beta coefficients of in-vehicle and out-of vehicle travel time ( $(-0.075,-0.078)$, compared to the joint RP/SP MNL model ( $-0.038,-0.036$ respectively)).

The Value of in-vehicle time was calculated as
$\mathrm{VOT}=\frac{\beta_{\text {invt }}}{\beta_{\text {cost }}} * 60$

1. 11.04 euros $/ \mathrm{hr}$ for car owners with the use of the MNL SP only model
2. 7.63 euros/hr for car non-owners with the use of the MNL SP only model
3. 8.7 euros/hr for the complete population (car and car non-owners) with the use of the joint RP-SP MNL model
4. 8.9 euros $/ \mathrm{hr}$ for the complete population (car and car non- owners) with the use of the RP-SP Nested Logit model

The Value of out-of-vehicle time was calculated as:
VOT $=\left(\frac{\beta_{\text {out-of-veh time }}}{\beta_{\text {cost }}}\right) * 60$

1. 11.32 euros/hr for car owners with the use of the MNL SP only model
2. 5.62 euros/hr for car non-owners with the use of the MNL SP only model
3. 8.24 euros $/ \mathrm{hr}$ for the complete population (car and car non-owners) with the use of the joint RP-SP MNL model
4. $9.27 \mathrm{euros} / \mathrm{hr}$ for the complete population (car and car non-owners) with the use of the RP-SP Nested Logit model

The Nested RP-SP model provides average estimations for the mean population compared to MNL SP only models and the Nested RP-SP MNL model.

All level-of-service variables are highly and significantly negative in the NL model. This implies that the 'in/out-of-vehicle travel time', the 'travel cost' and the 'transfer inconvenience' are associated with a disutility of choosing any travel mode decreases as time spent travelling, cost, and number of boarding times increase during subway closures.

Initially, the scale parameter for the bottom level (mode choice level) of the NL model is assumed to be 1. According to our estimation results of the NL model, the scale parameter for the upper level ( $\mathrm{rp} / \mathrm{sp}$ dataset) is 0.557 for the sp bus alternative, 0.419 for the sp car alternative (for car owners), 0.557 for the sp taxi alternative (for car owners), 0.578 for the sp bus alternative (for car non-owners), and 0.570 for the sp taxi alternative (car non- owners). This indicates that all sp alternatives are within the unit interval and should not share the same nest. Another interesting insight provided by the modespecific scale factors can be seen by noting that the ratio of the scale factors of all modes in the SP data set to that of car is greater than 1. Hence, these other modes, have error variances with an order of magnitude less than that of car, in the SP choice task. A likelihood ratio test clearly rejects the base MNL model that implicitly restricts the scale (IV) parameters to unity.

The dummy variable for male travelers of the NL model (included in the sp car alternative for car owners) yields a positive sign in the NL model, suggesting that the preference of this group is towards the car during metro disruptions. Low income travelers prefer, as expected, the bus; this holds for both car owners ( 0.555 ) and car nonowners (0.496) in the NL model. Age was not found to be statistically significant in any of the specifications of the NL model, possibly because age is frequently highly correlated with income. Working schedule flexibility was included as dummy variable in
the utility for car; the corresponding coefficient is negative and statistically significant in the NL model, indicating that travelers with 'fixed' schedules have a preference for car during disruptions, possibly because of the need to be, dependably, on time at work.

Employment status is also analyzed for the bus alternative (alternative specific for car owners and car non-owners), the car and the metro alternatives in the NL model. Instead, business oriented travelers (in the NL model) are less likely to use the metro ($1.118)$ during disruptions compared to the bus $(-0.276)$ and car ( -0.512 ). In other words, business oriented travelers traveling during metro closures are more likely to use a taxi rather than experience delays by traveling either on the disrupted metro network or on the congested road network.

The MNL model based on RP data has a statistically non significant in-vehicle travel time coefficient. This reflects the limited variation within the RP sample and the possible collinearity between time and cost. The SP models provide a statistically significant travel time (in-vehicle and out-of-vehicle travel time) coefficient. Using log likelihood values, goodness of fit of the estimated NL model is high (0.637).

### 7.8 Concluding Remarks

Despite the general importance of subway operational disruptions, this phenomenon has not been investigated thoroughly within existing literature. Very few comprehensive data sets exist that address travel patterns during subway closures. This study presents an effort at estimating alternative mode choice during metro network disruptions. This paper combines information on actual traveler experience regarding network closures with responses to a questionnaire regarding a hypothetical metro closure. An SP MNL model, an RP-SP joint MNL model and an RP/SP joint Nested Logit model were developed to analyze travel behaviors during a metro network closure and forecast intentions for traveling by alternative modes during such events, and it has been shown that in this application, the RP-SP joint Nested provides superior performance as it incorporates common random components for the RP/SP attributes.

Transfer inconvenience and travel cost are important for travelers when making decisions on mode selection during subway network closures. It appears that women are less willing to travel by car during subway closures. Low income travelers are also found to prefer travelling by bus during such closures.

We find that the WTP's for in-vehicle time and out-of-vehicle time are higher with joint RP/SP Nested Logit than with joint RP/SP MNL model. Policies based on the MNL model might be very different to those based on the Nested Logit model. For example, a policy might over invest in travel time savings instead of investing on park and ride or kiss and ride facilities, and local bus bridging services for the days of the subway disruption so as to encourage the use of public transport for all travelers. It is a common finding in the literature that estimations that control for unobserved heterogeneity find different WTP's than estimations that do not.

The main contribution of this study is the application of advanced econometric models (nested logit) on a novel topic of metro disruptions for the evaluation of impact of certain attributes like wait/walk, cost/transfer influence travel's behavior during such events. The results obtained from this study are realistic and we believe that they can be used for decision-making related to transport network disruptions. In particular, our analysis, suggests that improved schedule adherence of alternative transportation modes during metro closures, improved information and amenities are among the most effective ways that transport planners can use to reduce traffic congestion during metro closures. In our opinion, researchers should consider whether the factors varying in experiments impact the mean variance in utilities or impact only mean utilities. Practically, our findings suggest that the variability with which travelers choose an alternative travel mode during metro disruptions is not constant across individuals; this finding was possible because of the use of combined RP/SP data.

## 8. Conclusions and Suggestions for Future Research

### 8.1 Overview

In this chapter, the summary of the research is presented followed by specific research contributions and future research recommendations.

### 8.1.1 Summary of Research

This research contributes to the state-of-the-art by analyzing the altered travel patterns of metro passengers and the mobility behavior during and post-metro disruptions. This analysis is of particular interest because Metro systems form the backbone of the transportation system and every disruption, scheduled or not of the Metro system may result in serious disruption of the entire transportation network and potential loss of transport demand of the Metro system in the long-term. Despite the general importance of this phenomenon, to date there is limited literature with the detailed analysis of the altered travel patterns of metro passengers during and post metro network disruptions.

For this analysis travel data related to altered travel patterns during metro closures was collected, for three categories of travelers: a) travelers who remain on the partly disrupted network during the disruption and use the operating parts of the line, b) travelers who during closure shift to alternatives modes, and return to the metro system after line's restoration, and c) travelers who adopt the alternative mode even after the line's restoration. Revealed and Stated Preference methods were used to capture users' preferences regarding alternative ways of travel during a metro closure. The SP choice set of the hypothetical available alternatives during a 24 hr closure of the entire subway network was generated based on orthogonal design and the attributes of the level-ofservice variables were based on the RP data collected.

Primary analysis of the RP data showed that travel conditions (in terms of travel time) were worse for $50 \%$ of travelers during the closure. Similar percentage ( $40 \%$ ) reported encountering delays of up to 10 minutes. Only $10 \%$ of travelers reported that travel conditions were better than usual, possibly at a higher cost. During the 5-month closure, car use (either as driver or passenger) increased by $5 \%$, taxi use increased by $8 \%, 43 \%$ used the replacement bus services which run along the disrupted route, and $1 \%$ increased their use of the suburban rail line which runs parallel with the disrupted part of the line at much lower frequencies.

In this study, a binary logit model was also developed to explore the impact of trip and traveller characteristics on the "use of the partially disrupted Metro network during the closure of Metro Line 1". The analysis of the revealed preference data set yield that travelers who travel post-disruption for longer than 20 minutes have a lower likelihood of remaining on the Metro Line during the closure. Travelers who normally travel 60 minutes or more have a higher disutility for remaining on the disrupted network compared to travelers who normally travel between 20 and 60 minutes. Interestingly, travelers who make 2 or more transfers during the closure are twice as likely to remain on the Metro network compared to those who make 1 transfer. Interestingly, students have a higher probability of using Metro Line 1 during the disruption, probably due to cost constraints and time flexibility. The value of time for travelers who make 1 and 2 transfers, for students and for travelers who travel longer than 60 mins is low and this suggests that their disposal income is low and therefore it would have been interesting to collect travel cost data, which was difficult at the time of the study.

Using econometric models (Multinomial Logit, Multinomial Probit and Heteroskedastic Extreme Value Model) and appropriate elasticities based on Discrete Choice Theory, statistical tests were performed and concluded in the statistically significant parameters for each group of travelers and each model used based on the Stated Preference experiment. The targeted population was only travellers who travel at least once per week by subway. Analyses were undertaken separately for car owners and car non-owners. Results indicated that travelers who are regular subway travelers and have therefore been more affected by network disruptions, are less likely to shift to the car as a result of that disruption. Interestingly, elasticities of car demand with regard to fuel consumption and operating cost during subway closures appear higher compared to average short-run elasticities and closer to average long-run elasticies reported in the literature. As expected, public transport demand is less sensitive to cost changes (elasticity of -0.2 ) during a subway closure, while car demand is much more sensitive to a potential change in gas price. As expected, public transport demand is less sensitive to cost changes (elasticity of -0.2 ) during a subway closure, while car demand is much more sensitive to a potential change in fuel price and operating cost.

Younger travelers (age $<35$ years) are more willing to change their travel patterns. Results also indicate that the possibility of working in a flexible manner is important for some travelers and has to be considered in future closures by the transport operators and
policy makers. It is remarkable that $16 \%$ of the respondents canceled their programmed activity due to a Metro closure and only $1 \%$ postponed it their activity. A significant share of travellers ( $33 \%$ ) chose the car option during the Metro disruptions, while a $14 \%$ travelled by taxi. Value of travel time during disruptions is calculated highly variable between car-owners and car non-owners with the former been much higher than the latter ( 10.8 euros/hr versus 7.8 euros/hour). Elasticities of various level-of-service variables associated to the travelling modes in the SP choice during a subway disruption were determined for each alternative mode. The mean in-vehicle travel time elasticity for bus users is found to be -0.9 , for car-owners during a subway closure, while for car nonowners is -0.5 .

In addition to separately analysing the collected RP and SP data and to strengthen both data sources while discarding the weakness displayed by each, a combined SP-RP analysis was included in this dissertation. The inclusion of socio-demographic characteristics and the exposure of each traveller to different combination of values is a effective technique for expressing complex travel behavior. For this joint analysis a Nested Logit is used that allows partial relaxation of the assumption of independence among random components. Based on the estimated results, the basic assumption that travelers choices during subway distuptions are related to actual current and past choices is confirmed in the NL Joint RP-SP analysis as well. Among the 4 different models that were estimated at this stage (1 separate for RP data including assumptions on travel costs for the non-chosen alternatives, 1 for SP data and car owners, 1 for SP data and car non-owners, and 1 joint RP-SP Nested Logit, the Nested Logit was found to be the most appropriate and representative model. Most of the estimated coefficients were found to be statistically significant and stable with all level-of-service variables having negative signs. As expected the cost of travel was found to be the most influential attribute among level-of-service variables, with transfer inconvenience being the second most influential attribute in mode choice during subway disruptions. Waiting time at bus stations or taxi depots, parking-search time and in-vehicle time were found to equally influence the mode choice for work trips during subway disruptions.

In conclusion, the modelling process, used in this research and are obtained from the logit, probit and hev estimations can be effectively used by transport planners in evaluating and prioritising future closures in metro networks.

### 8.2 Research Contribution

Academically, the research herein explores a topic which has received little attention, most researchers have focused on empirical analysis of the impacts of Metro disruptions on travel patterns. The data collection are unique, in that it is the first time travel data regarding affected travelers are collected following the restoration of a Metro line, which service was temporarily disrupted for upgrading and compared to travel mode habits before the closure. By applying advanced econometric models on a novel topic of metro disruptions for the evaluation of impact of certain attributes like wait/walk, cost/transfer influence travel's behavior during such events, comparisons are made across different types of models which relax the IIA assumption.

While recognizing that this analysis suffers from biases and limitations, the major research contributions of the study are as follows:
I. An extensive RP survey was conducted along the disrupted Metro corridors to study the changes in travel patterns as a result of a planned 5-month closure of the metro network for upgrade works. This is the first time travel data regarding affected travelers are collected following the restoration of a Metro line, which service was temporarily disrupted for upgrading and compared to travel mode habits before the closure. A Binomial Logit model was calibrated using the collected RP data.
II. A uniquely design stated preference web-survey was designed to investigate alternative mode choices of Subway users for the period following a disruption, recording potential experiences with such events. We use information on previous traveler experience regarding network closures in combination with responses to a programmed subway closure where individuals are presented with a large set of options regarding mode used, travel time, travel cost, and number of transfers. We use information on previous traveler experience regarding network closures in combination with responses to a programmed subway closure where individuals are presented with a large set of options regarding mode used, travel time, travel cost, and number of transfers. However, since web-surveys suffer from a number of biases, a further investigation of this data collection method is useful in assessing the advantages and disadvantages for the collection.
III. The disaggregate behavioral model for mode choice has been formulated in such a manner as to explain better than other types of models travel behavior during Metro disruptions.
IV. Advanced model structures (MNL, MNP, HEV) were estimated to provide additional insight into the behavioral choices being made during Metro disruptions. We begin with the variables: in-vehicle time, out-of-vehicle travel time, travel cost and transfer inconvenience. We then develop more comprehensive models which include socio-demographic variables, and other trip-related characteristics, by designing and conducting an internet-based SP survey to analyze travel patterns during a hypothetical 24 hr Metro closure. This was combined with the collection of real data regarding actual changes in travel patterns due to planned or unplanned closure of Metro network. The alternatives considered during the Metro disruption were car, bus and taxi. This model explicitly addressed the systematic taste heterogeneity of the people by the introduction of dummy variables like, gender dummy, trip purpose dummy, high and low income dummy, frequency of subway use dummy, usual travel time dummy, and flexible working hours dummy. The SP survey calculated the effects of changes in travel prices, travel time and transfer inconvenience on metro travelers during Metro disruptions.
V. The research formulates different models for different population segments in an effort to reduce the errors in the aggregation process
VI. Considering the above, the results of our joint RP/SP questionnaire can shed light on traveler experiences during a closure and on the strategies people adopt when experiencing a disruption. This study is intended to provide a reasonable starting point for travel demand 4-stage modeling in specific situations of subway closures, by analyzing travelers altered behavior during closure and quantifying the effect of the closure on lost activities, cancelled trips and changes in demand for private and public transport. Models similar to the ones developed here can prove valuable when planning the delivery of subway upgrades and alternative transport options when lines are closed. Municipalities and transit authorities should learn from past experience and provide options (telework, carpooling, free
or discounted transit passes, etc) and have contingency plans to make traffic smoother for commuters, based on results presented.
VII. The travel behavior forecasts, under the hypothetical 24h closure of Metro network, can be utilized in assessing the feasibility of upgrading/restorating networks without significantly affecting the usual routes of millions of travelers.
VIII. From practical point of view, these models are likely to provide better ridership predictions for future closures and help in prioritizing the closures.

### 8.3 Future Research

The results support the necessity of combining RP and SP data if possible because of the fact that people tend to overstate their value of time when asked to state their choice in a hypothetical scenario.

The following recommendations can be taken into consideration to increase the validity of this research:
I. In this study the parameters of the mode choice model have been estimated sequentially. However, it is possible to better enhance the model by adding parameters in the SP survey like previous information on the disruption, possibility of cancelling the scheduled activity, possibility of postponing the start of the scheduled activity or even relocating for the period of the disruption.
II. In the present study, we collected RP data a few days after the restoration of the Metro service without having the opportunity of recollecting the same data a few months following the restoration to compare travel patterns. The collection of such data may shed light on the duration of this mode shift from public transport to car and taxi.
III. More advanced model structures (nested logit, cross nested, mixed logit) models can be estimated to better capture the traveler patterns during a Metro disruption.
IV. A 4-step model can be developed by incorporating trip generation, trip distribution and trip assignment steps of the 4 -step model with the mode choice model to better forecast the mode shift on existing or shuttle services during a Metro disruption.
V. In this research, people's WTP has been calculated based only for travel time, WTP for other attributes like comfort, safety, cycling facilities, cleaniness of the
vehicles, etc can be calculated by the design of more robust SP survey. Also SP survey was based on travel times as experienced from the RP survey without personalizing choice scenarios to respondents as it was difficult to recall the exact travel time due to the large number of strikes within the last month of the period when the survey was conducted. Hence we propose computer based adaptive surveys to present to respondents.
VI. Longer-term changes in passenger behavior (such as the relocation of homes or offices) were outside the scope of this work.

## Future suggestions and recommendation

We propose for future researchers to include the factor of working schedule and first define the term as it is believed that some people are not familiar with this idea. Maybe split the flexibility in groups of time i.e. flexibility of arriving late at work between 0-15 minutes, $15-30$ minutes, $30-60$ minutes, $>60$ minutes. This is considered a critical question and special consideration should be considered for final conclusions.

To assist transit operators dealing with unexpected or programmed closures without interrupting travelers' usual route, we propose the implementation of a telework project in coordination with employers.

In future research we could give the travelers the option in the SP experiment of "avoiding the rush-hours", "adjusting their schedule for family needs",

It should be noted that the public sector in Greece has a quite strict start time. Therefore while this variable may not be of significance for some employees in Greece, however it may be of significance for employees working under a flextime policy.

We propose conducting the survey including employees working under a flex time policy and employees working under a more strict start time policy. In this way, we can reduce any bias related to respondents who have not clearly understood the concept of flexible work schedule.

It is also important to include in the survey factors that may affect mode choice each travelers family activities, obligations and arrangements.

Among the questions that arise concerning the linkage of research to policy applications are the follow:

To what extent do different types of disruptions require different policy measures?
How much do we need to know about metro travelers' altered travel patterns in order to design effective policies? We list a few measures to minimize any social and environmental harm due to metro disruptions. The depth of the economic and financial crisis, requires immediate actions to be taken and reinforces the need for national cooperation between the government and transport operators so as to respond to the short term or long term effects of the disruptions especially during this difficult era of economic crisis. It is obvious that transport systems need to be reliable and sustainable in all times. In this regard, we propose the following:

- Politicians and transport operators should reconsider the transit fare policies, especially during metro network disruptions
- They should promote discounted tickets for public transit in the event of distuptions. In the days of disruptions, travelers argue with the transport operators regarding the lost fees of purchased travel cards. To deal with this we propose introducing rolling fare passes to compensate travelers for the lost days and avoid future loss in demand and revenue due to disappointment of the travelers. Note that in our case study regarding the 5-month partial closure of the metro network, the transport operators only provided free travel with a feeder bus line and allowed travelers with metro travel cards to travel on public transport for free. However, this policy was never put in place during an unexpected closure of the network or even during scheduled personnel strikes.
- They should simplify the fare ticketing collection and technology system so that in the event of a sudden disruption in the middle of the day, travelers can buy their tickets throught their smartphones or credit their card via phone.
- They should focus on applying effective marketing techniques which affect people's perception of transit system
- They should provide better information to travelers in the event of a disruption and provide them with alternative options.
- Provide also better integration of bus/metro system with Intelligent Transport System (ITS) technologies either via mobile/smartphones so that travelers can have better information regarding a potential closure of the metro line.
- The financial crisis has resulted in significant losses of income, thus making it difficult for low income users to afford traveling even by public transport. In this case, public transport operators should promote greater equity among different transportation user groups.
- Scientists should explore transition paths to promote sustainable transport during metro disruptions. They should also look at long-term measures and set long-term vital goals and key performance indicators so as to protect their companies from future loss in demand due to unreliability of the system network.

Unfortunately Europe is facing a very challenging era during the longest financial crisis after a decade of continuous economic growth and favorable quality of life. This continuous change/decrease in income levels should be taken seriously in minds as a unique opportunity of rearranging our way of thinking, and rethink our mobility behavior, through promoting sustainable ways of transport. Let's hope that we might see economic growth in the transport sector. What scientists were not able to do, crisis did it: take cars off the streets. This might be the answer. Sometimes through these situations, "push" policies can be taken on board; like promoting sustainable transport and forcing people to find more conventional and economic ways of travel to their destination even during a metro disruption.

## References

[1] Abdel-Aty, M.A., Kitamura, R., and Jovanis, P. (1995). Investigating effect of travel time variability on route choice using repeated-measurement Stated Preference data. Transportation Research Record, No. 1493, pp. 39-45.
[2] Ajzen, I., Brown, T.C., Rosenthal, L.H. and Lori, H. (1996). Information bias in contingent valuation: effects of personal relevance, quality of information and motivational orientation. Journal of Environmental Economics and Management, Vol. 30, Issue 1, pp. 43-57.
[3] Algers, S., Bergstroem, P., Dahlberg, M. \& Dillen, J. L. (1998). Mixed Logit Estimation of the Value of Travel Time, Working Paper, Department of Economics, Uppsala University, Uppsala, Sweden.
[4] Allenby, G. and Rossi, P. (1999). Marketing Models of Consumer Heterogeneity. Journal of Econometrics.
[5] Amey, A., Attanucci, J., and Mishalani, R. (2011). "Real-Time" Ridesharing- The Opportunities and Challenges of Utilizing Mobile Phone Technology to Improve Rideshare Services. Annual TRB Meeting 2011.
[6] Atasoy B., and M. Bierlaire (2012). An Air Itinerary Choice Model based on a Mixed RP/SP Dataset, Technical Report, TRANSP-OR 120426, Transport and Mobility Laboratory, Ecole Polytechnique Fédérale de Lausanne.
[7] Balog, N., Boyd, J., Caton, A. and James, E. (2003). The Public Transportation System Security and Emergency Preparedness Planning Guide. Report DOT-VNTSC-FTA-03-01. Washington DC, USA.
[8] Bamberg et al., (2003). Does habitual car use not lead to more resistance to change of travel mode? Transportation 30, pp.97-108.
[9] Ben-Akiva, M.E. and Lerman, S.R. (1985). Discrete Choice Analysis: Theory and Application to Travel Demand, MIT Press, Cambridge, Ma.
[10] Ben-Akiva, M.E. (1994). Combined Revealed and Stated Preferences Data-Marketing Letters, 5:4, pp335-350.
[11] Ben-Akiva, M. E., Bergman, M. J., Daly, A. J. and Ramaswamy, R. (1984). Modeling inter-urban route choice behaviour, in J. Volmuller and R. Hamerslag (eds), Proceedings from the ninth international symposium on transportation and trafic theory, VNU Science Press, Utrecht, Netherlands, pp. 299-330.
[12] Ben-Akiva, M. and T. Morikawa. (1990) Estimation of Switching Models from Revealed Preferences and Stated Intentions. Transportation Research, 24A(6), pp. 485-495.
[13] Ben-Akiva, M.E. Morikawa, T. and Shiroishi, F. (1991) Analysis of the reliability of preference ranking data. Journal of Business Research 23, pp. 253-268.
[14] Ben-Akiva, M.E, and Bierlaire, M. (1999). Discrete choice methods and their applications to short-term travel decisions. In Hall, R. (ed) Handbook of Transportation Science, pp. 5-34. Kluwer.
[15] Bhat, C.R., (1995). A heteroskedastic extreme value model of intercity travel mode choice. Transportation Research Part B, Vol. 29, Issue 6, pp. 471-483.
[16] Bhat C. R. (1998). Accomodating Flexible Substitution Patterns in Multi-dimensional Choice Modelling: Formulation and Application to Travel Mode and Departure Time Choice, Transportation Research Part B, Vol. 32, Issue 7, pp. 441-516.
[17] Bhat, C.R., Sardesai, R. (2006). The impact of stop-making and travel time reliability on commute mode choice; Transportation Research Part B Methodological, Vol. 40, Issue 9, pp. 709-730.
[18] Bjørnskau, T. (1999). Bothered by the Bus Strike? Nordic. Road and Transport Research, Vol. 2, Issue 11, pp 17.
[19] Bierlaire, M., Burton, D. and Lotan, T. (1993). On the behavioural aspects of modal choice. Technical Report 93/22, Department of Mathematics, FUNDP.
[20] Bliemer, M.C.J., Rose, J.M., Hensher, D.A. (2009). Efficient stated choice experiments for estimating nested logit models, Transportation Research Part B, Vol. 43, Issue 1, pp. 19-35.
[21] Blumstein, A., and Miller, H.D. (1983). Making do: the effects of a Mass Transit Strike on Travel Behavior. Transportation, 11: pp. 361-382.
[22] Bonsall, P., and Dunkerley, C. (1997). Use of Concessionary Travel Permits in London: Results of a Diary Survey". Proceedings of the 25th annual AET European Transport Conference, Public Transport Planning and Operations (Seminar G) P416, pp. 99-116.
[23] Boyd, A., Maier, P. and Caton, J. (1998). Critical Incident Management Guidelines. Report FTA-MA-26-7009-98-1. Washington DC, USA.
[24] Bradley, M.A. and Daly, A.J. (1994) Use of the logit scaling approach to test rank order and fatigue effects in Stated Preference data. Transporation 21(2), pp.167-184.
[25] Bregman S., (2011). Overcoming Barriers Using Social Media in Public Transportation. Summary of Findings from TCRP Synthesis SB-20. Annual TRB Meeting 2012.
[26] Carlsson, F., and Martinsson, P. (2001). Do hypothetical and actual marginal willingness to pay differ in choice experiments? Journal of Environmental Economics and Management, Vol. 41, Issue 2, pp. 179-192.
[27] Carlsson F., Mørbak, M.R and Olsen, S.B. (2012). The first time is the hardest: A test of ordering effects in choice experiments. Journal of Choice Modelling, Vol. 5, Issue 2, pp. 19-37.
[28] Cascetta, E., Nuzzolo, A. and Biggiero, L. (1992). Analysis and modeling of commuters' departure time and route choice in urban networks, Proceedings of the second international Capri seminar on urban traffic networks.
[29] Cirillo, C. and Axhausen, K. W. (2004). Evidence on the distribution of values of travel time savings from a six-week diary, Arbeitsbericht Verkehrs- und Raumplanung 212, IVT, ETH Zurich.
[30] Chopra, S.C, Sodhi, M.S, (2004). Managing risk to avoid supply-chain breakdown. MIT Sloan Management Review, Volume 46, Issue 1, pp. 53-61.
[31] Coindet, J-P. (1998). Home-to-work trips during the Transportation Strikes in Ile-de-France at the end of 1995. Journal of Transportation and Statistics, Vol. 1 Issue 3, pp. 4351.
[32] Council Directive 2008/114/EC of 8 December 2008 on the Identification and Designation of European Critical Infrastructures and the assessment of the need to improve their protection, Official Journal of the European Union, L345/75
[33] Couper, M.P. (2000). Web surveys; a review of issues and approaches. Public Opinion Quarterly, Vol. 6, Issue 4, pp. 464-94.
[34] Curtis, C., and Perkins, T. (2006). Working Paper, Travel behaviour, A review of recent literature, Urbanet, Curtin University of technology
[35] Daganzo, C. (1979). Multinomial Probit: The theory and its application to Demand Forecasting. Academic Press. New York.
[36] Darmamin T, Calvin L, and Gan, H. (2010). Public railway disruption recovery planning: A new recovery strategy for Metro Train Melbourne. 11 $1^{\text {th }}$ Asia Pacific Industrial Engineering and Management Systems Conference Proceedings.
[37] Day, B., Bateman, I., Carson, R., Dupont, D., Louviere, J.J, Morimoto, S., et al. (2012). Ordering effects and choice set awareness in repeat-response Stated Preference studies, Journal of Environmental Economics and Management, Vol. 63, Issue 1, pp. 73-91.
[38] De Jong, G., and Gunn, H. (2001). Recent evidence on car cost and time elasticities of travel demand in Europe. Journal of Transport Economics and Policy, Vol. 35, Part 2, pp. 137-160.
[39] Department for Transport. (2011). Winter Resilience in Transport: an assessment of the case for additional investment. London, UK. Accessed online November 2012. http://assets.dft.gov.uk/publications/winter-resilience-in-transport/an-assessment-of-the-case-for-additional-investment.pdf.
[40] Devine, S.A., Bucci, J.A. and Berman, D.J. (1992). Traffic Management during the I195 Providence River Bridge Repair Project. Transportation Research Record, No 1360, pp. 1-3.
[41] Dhar, R. (1997). Consumer preference for a no-choice option, Journal of Consumer Research,
[42] Dhar, R., and Simonson, J. (2003). The effect of forced choice on choice, Journal of Marketing Research, Vol. 40, pp. 146-160.
[43] Dilman, D. (2000). Constructing the Questionnaire; Mail and Internet Surveys. New York, John Wiley and Sons, Inc, New York
[44] Dissanayake, D., and T. Morikawa.(2000). Travel Demand Models with the RP/SP Combining Technique for the Developing Countries, The International Conference CODATU IX, Mexico, pp. 103-107.
[45] Dissanayake, D., and T. Morikawa. (2001) A Combined RP/SP Nested Logit Model to Investigate Household Decisions on Vehicle Usage, Mode Choice and Trip Chaining, Journal of Eastern Asia Society forTransportation Studies, Vol. 4(2), 2001, pp. 235-244.
[46] Dissanayake, D. (2001) Urban Transport Policy Analysis for Developing Countries Considering Household Choices of Modes, Trip Chaining and Vehicle Ownership, Doctoral Dissertation, Department of Civil Engineering, Nagoya University, Japan.
[47] Dissanayake, D., and Morikawa, T. (2010). Investigating household vehicle ownership, mode choice and trip sharing decisions using a combined revealed preference/Stated Preference Nested Logit model: case study in Bangkok Metropolitan Region; Journal of Transport Geography, Vol. 18 pp. 402-410.
[48] Domencich, T. A. and McFadden, D. (1975). Urban Travel Demand: A Behavioral Analysis. North-Holland Publishing Co., 1975. Reprinted 1996.
[49] Efthymiou, D., and Antoniou, C. (2012). Use of Social Media for Transport Data Collection. Procedia-Social and Behavioral Sciences, Vol. 48. pp. 775-785.
[50] European Foundation for the Improvement of Living and Working Conditions. (2010). Telework in the European Union. Ireland. Accessed online 31 January 2013. Available at: http://www.eurofound.europa.eu/eiro/studies/tn0910050s/tn0910050s_3.htm
[51] Fasolo, B., Zhifang, N., Philips, L.A. (2008). A Study of the Impact of the July Bombings on Londoner's Travel Behaviour, CREATE-LSE Award
[52] Fawkes, T., Wardman, M. (1988). The design of Stated Preference travel choice experiments-A comparison of revealed preference and Stated Preference models of travel behavior. Journal of Transport Economics and Policy, Vol. 22, No.1, pp. 27-44
[53] Fujii, S., Garling, T. and Kitamura, R. (2001). Changes in Driver's Perceptions and Use of Public Transportation during a Freeway Closure: Effects of Temporary Structural Change on Cooperation in a Real-Life Social Dilemma. In Environment and Behavior, Vol. 33, Issue 6: pp. 796-808.
[54] Gerike, Bamberg, S and Schmidt, P. (1994). 'Auto oder Fahrrad: Empirischer Test einer Handlungstheorie zur Erklärung der Verkehrsmittelwahl', Kölner Zeitschrift für Soziologie und Soziopsychologie, pp. 80-102.
[55] Gigerenzer, G. (2006). Out of the frying pan into the fire: behavioral reactions to terrorist attacks, Risk Analysis, Vol. 26, No. 2, pp. 347-351.
[56] Goodwin, P.B. (1992). Review of new demand elasticities with special reference to short and long run effects of price changes. Journal of Transport Economics and Policy, Vol. 26, No. 2, May, pp. 155-171.
[57] Greene, W.H., and Hensher, D.A. (2010). Does scale heterogeneity across individuals matter? An empirical assessment of alternative logit models. Transportation, Vol. 37, No. 3, pp. 413-428
[58] Grigolon, A.B., Kemperman, A.D.A.M. and Timmermans, H.J.P. (2011). Using Web2.0 Social Network Technology for Sampling Framework Identification and Respondent Recruitment: Experiences with a Small-Scale Experiment, Annual TRB Meeting 2011.
[59] Harris, N.G. and Ramsey, J.B.H. (1994). "Assessing the Effects of Railway Infrastructure Failure", Journal Operational Research Society, Vol. 45 pp. 635-640.
[60] Harrison, G. W. (2006). 'Experimental evidence on alternative environmental valuation methods'. Environmental and Resource Economics 34(1), 125-162.
[61] Heinen, E., van Wee, B. and Maat, K. (2010). 'Commuting by Bicycle: An Overview of the Literature', Transport Reviens, Vol 30, No. 1, pp. 59-96.
[62] Heiss F. (2002) Structural Choice Analysis with Nested Logit Models. The Stata Journal, Vol. 2, Issue 3, pp. 227-252.
[63] Hensher, D. A. (2001a). Measurement of the valuation of travel time savings, Journal of Transport Economics and Policy 35(1), pp. 71-98.
[64] Hensher, D.A. (2001b). The sensitivity of the valuation of travel time savings to the specification of unobserved effects', Transportation Research 37E, pp. 129-142.
[65] Hensher, D.A. (2001c). The valuation of commuter travel time savings for car drivers: evaluating alternative model specifications, Transportation, Vol. 28, pp. 101-118
[66] Hensher, D.A. (1996). Extending valuation to controlled value functions and non-uniform scaling with generalized unobserved variances. Working Paper ITS-WP-96-9, Institute of Transport Studies, The University of Sydney.
[67] Hensher, D.A, Rose, J.M. and Greene, W.H. (2005). Applied Choice Analysis. A Primer. Cambridge University Press. 2005.
[68] Hensher, D.A, Bradley, M. (1993). Using stated choice data to enrich revealed preference discrete choice models, Marketing Letters 4, pp. 139-152
[69] Hensher, D.A. (1994). Stated Preference analysis of travel choices: the state of practice. Transportation, Vol. 21, pp. 107-133
[70] Hensher, D.A., (2010). Hypothetical bias, choice experiments and willingness to pay, Transportation Research Part B, pp. 735-752.
[71] Hensher. D. A. and Johnson, L.W. (1981). Applied discrete-choice modeling. Crook Helm (London and New York).
[72] Hensher, D.A. and Barnard, P.O. (1990). The orthogonality issue in stated choice designs. In: Fischer
[73] Hendrickson, C. and Plank, E. (1984). The flexibility of departure times for work trips, Transportation Research Part A: Policy and Practice, Vol. 18, Issue 1, pp. 25-36.
[74] Hess, S. (2004). Estimation of Value of Travel Time Savings using Mixed Logit Models. Transportation Research Part A, Policy and Practice: 39(2-3), pp.221-236.
[75] Hess, S. (2005). Advanced Discrete Choice Models with Applications to Transport Demand, PHD thesis, University of London.
[76] HM Treasury (2011). The Green Book. Appraisal and Evaluation in Central Government. Available online at:http://www.hm-treasury.gov.uk/d/green book annex2 250711.pdf Accessed on August 10 $0^{\text {th }}, 2013$.
[77] Jenelius, E., and Mattsson, L.G. (2012). Road network vulnerability analysis of areacovering disruptions: A grid-based approach with case study, Transportation Research Part A: Policy andPractice, Vol. 46, Issue 5, pp. 746-760.
[78] Johansson, M.V., Heldt, T. and Johansson, P. (2006). 'The effects of attitudes and personality traits on mode choice', Transportation Research Part A: Policy and Practice, Vol 40, No. 6, pp. 507-525.
[79] Johnson, N. and Kotz, S. (1970). Distributions in Statistics: Continuous Univariate Distributions (Chapter 21). Wiley, New York
[80] Jovanis, P.P. and Moore, A. (1984). Models of Employee Work Schedule, Proceedings of the Ninth International Symposium on Transportation and Traffic Theory.
[81] Kahneman, D., Slovic, P. and Tversky, A. (1982). Judgement Under Uncertainty: Heuristics and Biases. New York: Cambridge University Press
[82] Kaaplowitz, M.D., Hadlock T.D., Levine, R. (2004). A comparison of web and mail survey response rates. Social Sciences, Public Opinion Quarterly, Vol. 68, Issue 1, pp. 94101.
[83] Kepaptsoglou, K. and Karlaftis, M.G. (2010). A Model for Analyzing Metro Station Platform Condition Following a Service Disruption. Intelligent Transport Systems (ITSC) 13th International IEEE. Madeira Island, Portugal: 189-1794.
[84] Krizek, K.J., and El-Geneidy, A. (2013). Segmenting Preferences and Habits of Transit Users and Non-Users. Journal of Public Transportation, Vol. 10, No. 3, 2007.
[85] Kroes, E.P., Sheldon, R.J. (1988). Stated Preference methods; An introduction, Journal of Transport Economics and Policy, Vol. 22, pp. 11-25.
[86] Ladenburg, J. and Olsen, S. B. (2008). Gender-specific starting point bias in choice experiments: Evidence from an empirical study. Journal of Environmental Economics and Management, 56(3), pp. 275-285.
[87] Lapierre, E. (1998). "What is the best car sharing organization for Ile de France?". Proceedings of the 26th annual AET European Transport Conference Policy Planning and Sustainability (Seminar C) P422: pp. 189-199.
[88] Lari, A. (2012). Telework/Workforce flexibility to reduce congestions and environmental degradation? Social and Behavioral Sciences, Vol. 48, pp. 712-721, University of Minnesota, Minneapolis, USA.
[89] Lo, S.C. and Hall, R. (2006). Effect of the Los Angeles transit strike on highway congestion. Transportation Research Part A: Policy and Practice, Vol. 40, Issue 10: 903-917. Accessed online November 2012. doi:10.1016/j.tra.2006.03.001.
[90] London Assembly Transport Committee (2011). The State of the Underground. http://www.london.gov.uk/sites/default/files/FINAL\ REPORT_3.pdf Accessed online September 2012.
[91] London Assembly Transport Committee, (2012). Minimising Disruption on London Underground Upgrading the Piccadilly line. A discussion paper prepared for the London Assembly Transport Committee.
http://legacy.london.gov.uk/assembly/reports/transport/too-close-for-comfort-
TravelWatch.rtf Accessed online July 2012
[92] London Assembly Transport Committee, (2009). Too close for comfort. Passengers' experience of the London Underground. Accessed online November 2012.
http://legacy.london.gov.uk/assembly/reports/transport/too-close-for-comfort.pdf
[93] Louviere, J.J., Hensher, D.A., and Swait, J.D. (2000). Stated Choice Methods-Analysis and Application, Cambridge University Press, 2000, Cambridge
[94] Louviere, J.J., (2006). What you don't know might hurt you: some unresolved issues in the design and analysis of discrete choice experiments. Environmental and Resource Economics, Vol. 34, Issue 16, pp. 173-188.
[95] Li, L., Xiong, J., Dong, Z., Bai, Y. and Wu, B. (2013). Exploring the Factors Affecting Current Transit Passengers' Loyalty by Structural Equation Model: Case Study of Shanghai, China. TRB 2013 Annual Meeting.
[96] Lotan, T. (1992). Modeling route choice behavior in the presence of information using concepts from fuzzy set theory and approximate reasoning, PhD thesis, Massachusetts Institute of Technology.
[97] Mabit, S. L. (2010). RP/SP estimation including reference-dependent preferences. in: Proceedings European Transport Conference 2010, Glasgow.
[98] Mannering, F, Murakami, E. and S. G. Kim. (1994). Temporal Stability of Travelers'Activity Choice and Home-stay Duration: Some Empirical Evidence, Transportation, Vol. 21, pp. 371-392.
[99] Manski F.C. and S.R. Lerman. (1977). "Estimation of Choice Probabilities from Choice-Based Samples." Econometrica, 45: 1977-1989.
[100] Marmo, M. (1990). "More profile than courage: the New York City Transit strike of 1966". New York. State University of New York Press.
[101] McCulloch, R.E, and Rossi, P.E. (1993). An exact likelihood analysis of the multinomial probit model. Journal of Econometrics, Vol.64, pp. 207-240.
[102] McFadden, D. (1974). Conditional Logit Analysis of Qualitative Choice Behavior. P. Zarembka (editor), Frontiers in Econometrics, New York: Academic Press
[103] McCafferty, D. and Hall, F. L. (1982). The use of multinomial logit analysis to model the choice of time of travel, Economic Geography, Vol. 58, Issue 3, pp. 236-246.
[104] Metro de Madrid. (2010). Annual Report Metro de Madrid 2010. http://www.metromadrid.es/export/sites/Metro/comun/documentos/memoria/2010/ Memoriaingles2010.pdf. Accessed only July 2012 (Mesa sto keimeno na to grapso Metro de Madrid, 2010).
[105] Meyer, M. D. and Belobaba, P. (1982). Contingency Planning for Response to Urban Transportation System Disruptions, Journal of the American Planning Association, Vo. 48, Issue 4, pp. 454-465.
[106] Mitchell, R.C., and Carlson, R.T. (1989). Using surveys to value public goods: The contingent valuation method. Baltimore: Johns Hopkins Press
[107] Morikawa, T. Incorporating Stated Preference Data in Travel Demand Analysis, Doctoral Dissertation, Department of Civil Engineering, MIT, 1989.
[108] Munizaga M., Heydecker B.G., and Ortuzar J. (2000). Representation of heteroskedasticity in discrete choice models, Transportation Research Part B, Vol. 34 pp. 219-240.
[109] Nam, D., Lee, J., Dunston, P., and Mannering, F. (1999). Analysis of the Impacts of freeway reconstruction closures in urban areas. Transportation Research Record, No 1654, pp. 161-170.
[110] Nicholson, W. (1978). Microeconomic Theory. Dryden Press, Hinsdale, IL.


[112] Ortuzar, J. de D., and Willumsen, L.G. (1994). Modeling Transport, 2nd ed. Wiley, Chichester.
[113] Ott, M., Slavin, H., and Ward, D. (1980). Behavioral Impacts of Flexible Working hours. Book, Transportation Research Record, No 767, pp. 1-6.
[114] Owen, J.D., (1979) Working Hours : An Economic Analysis. Lexington Books
[115] Parent-Thirion, A., Fernández Macías, E., Hurley, J. and Vermeylen, G. (2007). Fourth European Working Conditions Survey, Luxembourg, Office for Official Publications of the European Communities, 2007.
[116] PbIVVS. (1984). "Effects on Traffic and Transportation of a strike at HTM", Main report, Projectbureau Integrale Verkeers - en Vervoerstudies, Ministrie van Verkeer en Waterstaat, The Hague.
[117] Pearmain, D., Swanson, J., Kroes, E. and Bradley, M. (1991). Stated Preference Technique - A Guide to Practice (2 ${ }^{n d}$ Ed.), Steer Davies Gleave and Hague Consulting Group
[118] Pender, B., Currie G., Delbosc A., and Shiwakoti, N. (2012). Planning for the Unplanned: An International Review of Current Approaches to Service Disruptions Management of Railways; Australasian Transport Research Forum 2012 Proceedings, Perth, Australia
[119] Pells, S. (1987). "The Evaluation of Reduction in the Variability of Travel Times on the Journey to Work", PRTC Seminar C 7-11 Sept. 1987.
[120] Pnevmatikou A. M., and Karlaftis M.G. (2011). Demand changes from Metro line closures, European Transport Conference Proceedings, Scottland
[121] Pnevmatikou, A. M. and M.G. Karlaftis. (2013). Subway closures and traveler alternative mode choices: an empirical investigation, Advances in Transportation Studies, Vol. 31, pp. 35-52.
[122] Polydoropoulou, A. and M. Ben-Akiva. (2001). Combined RP/SP Nested Logit Access/Mode Choice Model for Multiple Mass Transit Technologies. CD-ROM 80th Transportation Research Board Annual Meeting, Washington D.C.
[123] Rose, J.M. and Bliemer, M.C.J. (2004). 'The design of stated choice experiments: the state of practice', Working Paper, Institute for Transportation Studies, The University of Sydney.
[124] Rubin G.J., Brewin C.R., Grenberg N., and Simpson J. (2005). Psycological and behavioura; Reactions to the bombings in London on 7 July 2005: cross sectional survey of a representative sample of Londoners. BMJ, 331 (7517), pp. 606-611.
[125] Sanko, N., (2001). Guidelines for Stated Preference Experiment Design (Professional Company Project in Association with RAND Europe), Ecole National des Ponts et Chaussees.
[126] Sermpis, D., Babis, C., and Theofilis, I.. (2007). The impact of a transit strike on the traffic patterns in the Athens road network. Accessed online September 2012. www.patt.gov.gr/main/attachments2/4884_05.pdf.
[127] Shaikh and Larson, (1998). Methods for Combining travel cost and contigent valuation data-Prepared for the World Congress of Environmental and Resource Economists
[128] Scheiner J, and Holz-Rau, C. (2012). Gendered travel mode choice: a focus on car deficient households, Journal of Transport Geography, Vol. 30
[129] Sheldon, R. J., and Steer, J.K. (1982). The Use of Conjoint Analysis in Transport Research, Paper presented to the 1982 PTRC Summer Annual Meeting, Warwick.
[130] Sobel, K. L. (1980). Travel Demand Forecasting by using the Nested Multinomial Logit Model, In Transportation Research Record, Vol. 775, 1980, pp.48-55.
[131] Steer, J. K. and Willumsen, L. (1981). An investigation of Passenger Preference Structures. Paper presented to the 1981 PTRC Summer Annual Meeting, Warwick.
[132] Stopher, P.R., Meyburg A.H. and Brög, W. (editors) (1981). Travel behavior research: a perspective. New Horizons in Travel Behavior Research Lexington Books, D.C. Heath and Co., Lexington, Massachusetts.
[133] Talvitie A. (1978). Planing Model for Transportation Corridors, In Transportation Research Record 673, pp. 106-112.
[134] TRADEMCO - ADO S.A., (2010). Passenger Survey in Athens Transport Network, Attiko Metro S.A.
[135] Train, K., and Wilson, W. (2009). Monte Carlo analysis of SP-off-RP data, Journal of Choice Modelling, Vol. 2, Issue 1, pp.101-117.
[136] Train, K. (2003), Discrete Choice Methods with Simulation, Cambridge University Press, Cambridge, MA.
[137] TRB, (2008). The Role of Transit in Emergency Evacuation: Special Report 294 (Free Executive Summary) http://www.nap.edu/catalog/12445.html
[138] UrbanRail (2012), Urban Rail Official Web Site
http://www.urbanrail.net
[139] Urban Transportation Showcase Program, (2012). TDM Strategies during transportation disuptions and episodic events. Issue paper 75, accessed online October 2012. Source:
http:// fcm.ca/Documents/case-studies/GMF/Transport-
Canada/TDMStrategies_EN.pdf
[140] Valdés-Diaz, D.M, Martínez, F.E., Suárez, S.B. and Colucci, B. (2005). Contigency planning for Response to Urban Transportation System Disruptions, Journal of the American Planning Association, Vol. 48, Issue 4, 454-465.
[141] Van Excel, N.J.A., and Rietveld, P. (2001). Public transport strikes and travel behaviour, Transport Policy, Vol 8, Elsevier, pp. 237-246.
[142] Van Exel, N.J.A. and Rietveld. P. (2009). When strike comes to town: anticipated and actual behavioural reactions to a one-day, pre-announced, complete rail strike in the Netherlands. Transportation, Part A, Vol. 43, pp. 526-535.
[143] Van Loon, R., Rouwendal J., and Rietveld, P. (2011). "Vacation Behaviour: Frequency, Destination Choice and Expenditure Level," ERSA conference papers ersa10p921, European Regional Science Association.
[144] Wardman, M., (1988) A comparison of Revealed Preference and Stated Preference Models of Travel Behavior, Journal of Transport Economics and Policy, Vol22, pp71-91.
[145] Washington, S., Karlaftis, M.G., and Mannering, F.L. (2010). Statistical and Econometric Methods for Transportation Data Analysis, $2^{\text {nd }}$ edition. Chapman \& Hall/CRC, Boca Raton, FL.
[146] World Health Organisation
http://www.who.int/gho/urban_health/situation_trends/urban_population_growth_te xt/en/index.html

Accessed online January 2013
[147] Wesemann, L., Hamilton, T., Tabaie, S., and Bare, G. (1996). Cost-of-delay studies for freeway closures caused by Northbridge earthquake. Transportation Research Record, No. 1559, pp.67-76
[148] Windle, R. \& Dresner, M. (1995). 'Airport choice in multi-airport regions', Journal of Transportation Engineering 121(4), 332-337.
[149] Zeng, L.A. (2000). Heteroskedastic generalized extreme value discrete choice model. Sociological Methods and Research, Vol. 29, pp.119-145
[150] Zhu, S., Levinson, D. (2008). Planned and unplanned disruptions to transportations networks, Transportation Research Synthesis, Minnesota Department of Transportation.
[151] Zhu, S., and Levinson, D.M. (2010). A review of research on planned and unplanned disruptions to Transportation Networks. Paper presented at the $89^{\text {th }}$ Annual Transportation Research Board Meeting, Washington D.C.
[152] Zhu, S., Levinson, D., Liu, H.X., Harder, K. (2010). The traffic and behavioral effects of the I-35W Mississipi River bridge collapse. Transportation Research Part A, Vol. 44, pp.771-784
[153] Zhu, S., Levinson, D. (2011). Disruptions to transportation networks: a review. In Levinson D, Liu H, Bell M (eds) Network reliability in practice. Springer, New York, pp 5-20.

## Websites

http://onlinepubs.trb.org/onlinepubs/nchrp/cd-22/v2chapter5.html www.choice-metrics.com

Appendix A-Travel Diary Survey-Greek





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| ETAemoz EIZOAOY | इTAEMOE EEOLOY |  |
| যtaemor elioacy | যTAeMOz EEOAOY |  |








| IX (08пүо́c) | Taki. | Проаотtкко்¢ |
| :---: | :---: | :---: |
|  | Метро́ | Motooukiżto |
| пosinato |  | Alro |



|  | عтрó | Motoorket |
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| Поб̇¢¢ато |  | Aldo |


|  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Eza日uóc <br>  |  | £täuо́с aroßißaors | TEスıxóc проорıбио́¢ | Мह்бо апохш்рпапя |  |  |  |
|  |  |  |  |  |  | $\begin{aligned} & \hline \text { Epyacia } \\ & \text { Evraiઠ } \\ & \hline \end{aligned}$ | $\begin{aligned} & \text { Kovav } \\ & \text { Adroc } \\ & \hline \end{aligned}$ |  |

Appendix B-Online Personal Survey and Stated Choice Experiment-Greek
As distributed to survey participants (The questionnaire was build on a web-based platform)

## 

 $М \varepsilon \tau \eta \mu \varepsilon ́ \theta o \delta o \tau \eta \varsigma \Delta \varepsilon \delta \eta \lambda \omega \mu \varepsilon ́ v \eta \varsigma$ Протí $\boldsymbol{\eta} \sigma \eta \varsigma$A' MEPOL
A1. Фú 2 o :

| Av $\delta \rho \alpha \varsigma$ |  |
| :--- | :--- |
| Гvvaíк $\alpha$ |  |



| Avepros |  |
| :---: | :---: |
|  |  |
|  |  |
| Maөŋтп́s |  |
| Фoıтทัท́s |  |
| $\Sigma \tau \rho \alpha \tau 1 \omega \tau 1 \kappa$ ¢́s |  |
| Оєккко́ |  |
|  |  |



| 0 |  |
| :--- | :--- |
| $1-3$ |  |
| $3-5$ |  |
| $>5$ |  |





| Лєळ¢орві́о/Тро́лєӥ | Проабтıако́ऽ | Поби́入ато |  |
| :---: | :---: | :---: | :---: |
| T¢Évo (НГАП) | T $\alpha$ gí | Пцऽֹ́ |  |
| Mєт ${ }^{\text {ó }}$ | T $\rho \alpha \mu$ | A $\lambda \lambda$ o |  |




| $5-15 \lambda \varepsilon \pi \tau \alpha ́$ |  |
| :--- | :--- |
| $16-30 \lambda \varepsilon \pi \tau \alpha ́$ |  |
| $31-45 \lambda \varepsilon \pi \tau \dot{\alpha}$ |  |
| $46-60 \lambda \varepsilon \pi \tau \dot{\alpha}$ |  |
| $61-75 \lambda \varepsilon \pi \tau \dot{\alpha}$ |  |
| $76-90 \lambda \varepsilon \pi \tau \dot{\alpha}$ |  |
| $>90 \lambda \varepsilon \pi \tau \alpha \dot{\alpha}$ |  |



| K $\alpha \theta \varepsilon \mu \varepsilon ́ \rho \alpha$ |  |
| :---: | :---: |
| 1-2 ¢орغ́s $\tau \eta \vee \varepsilon \beta \delta о \mu \alpha \delta^{\prime} \alpha$ |  |
|  |  |
| 1 ¢оро́ то $\mu$ ¢́vа |  |
| 2-3 ¢оре́¢ то $\mu$ ¢́vа |  |
|  |  |



| 0 |  |
| :--- | :--- |
| 1 |  |
| 2 |  |
| 3 |  |
| 4 |  |
| $>=5$ |  |




| NAI |  |
| :--- | :--- |
| OXI |  |

## A10. Tı $\alpha \kappa \rho ı \beta \dot{\varsigma} \varsigma \sigma v \vee \dot{\beta} \beta \eta ;$

 біо́ $\rho \kappa \varepsilon 1 \alpha \tau \eta \varsigma ~ \eta \mu \varepsilon ́ \rho \alpha \varsigma$.

| NAI |  |
| :--- | :--- |
| OXI |  |

A12. Акорю́ба兀є ко́лою $\mu \varepsilon ́ \rho о \varsigma ~ \tau \eta \varsigma ~ \mu \varepsilon \tau \alpha к і ́ v \eta \sigma \eta ́ \varsigma ~ \sigma \alpha \varsigma ~ \lambda o ́ \gamma \omega ~ \alpha v \tau \eta ́ \varsigma ~ \tau \eta \varsigma ~ \pi \lambda \eta \rho о \varphi о р i ́ \alpha \varsigma ; ~ ;$

| NAI |  |
| :--- | :--- |
| OXI |  |



| NAI |  |
| :--- | :--- |
| OXI |  |



| NAI |  |
| :--- | :--- |
| OXI |  |

А15. Поъ६ऽ $\varepsilon v \alpha \lambda \lambda \alpha \kappa \tau 兀 \kappa \varepsilon ́ \varsigma ~ \varepsilon i ́ \chi \alpha \tau \varepsilon ;$

| $1^{n} \varepsilon v \alpha \lambda \lambda \alpha \kappa \tau \iota \kappa \dot{\prime}$ <br>  |  |
| :---: | :---: |
| IX |  |
| Meтрó |  |
| НГАП |  |
| T $\alpha$ ¢́ |  |



A16. Пот $\alpha$ عv $\alpha \lambda \lambda \alpha \kappa \tau 1 \kappa \eta ́ ~ \tau \varepsilon \lambda ı \kappa \alpha ́ ~ \varepsilon \pi ı \lambda \varepsilon ́ \xi \alpha \alpha \tau ;$

| $1^{\eta} \varepsilon v \alpha \lambda \lambda \alpha \kappa \tau \iota \kappa \eta$ |  |
| :--- | :--- |
| $2^{\eta} \varepsilon v \alpha \lambda \lambda \alpha \kappa \tau 1 \kappa \eta$ |  |


A17. 'Еұєєє IX $\alpha \cup \tau о к і ́ v \eta \tau о ; ~$

| NAI |  |
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| OXI |  |

Av NAI $\pi \rho \sigma \chi \omega \rho \eta ์ \sigma \tau \varepsilon \sigma \tau \eta \nu$ E $\rho \dot{\tau} \tau \eta \sigma \eta$ A18, $\alpha \lambda \lambda \iota \omega ́ \varsigma ~ \sigma \tau \eta \nu \mathrm{~A} 27$.


 ПАРАТІ@ЕNTAI 9 YПОӨЕТIKA ГENAPIA)
 крıти́ $\nless \alpha$ );


A28. Н $\lambda$ ıкí $\alpha$

| $15-18$ |  | $46-55$ |  |
| :--- | :--- | :--- | :--- |
| $19-25$ |  | $55-65$ |  |
| $26-35$ |  | $>65$ |  |
| $36-45$ |  |  |  |
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| へıүótєро $\alpha \pi$ ó 600 عטคஸ́ |  |
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| 1500-2000 عup(́ |  |
| >2000 £טрต́ |  |



| $\Delta \eta \mu$ отко́/Гvцло́бьо |  |
| :---: | :---: |
| ムи́кєı |  |
| Колдغ́ $\gamma 10$ |  |
| AEI/TEI |  |
| Kর́тохо¢ $\mu \varepsilon \tau \alpha \pi \tau \cup \chi 1 \alpha \kappa о v ์ ~ \delta ı \pi \lambda \omega ́ \mu \alpha \tau о \varsigma ~$ |  |
|  |  |
|  |  |



| NAI |  |
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| OXI |  |


[^0]:    ${ }^{1} \mathrm{http}: / /$ www.who.int/gho/urban_health/situation_trends/urban_population_growth_text/en/

[^1]:    ${ }^{1}$ WEB ID, 2010, Focus Bar, under the supervision of the Observatory for the Greek Information Society.

[^2]:    ${ }^{1}$ http://onlinepubs.trb.org/onlinepubs/nchrp/cd-22/v2chapter5.html.

[^3]:    2 See Bolduc (1999) for a more detailed description of variance normalisation and simulated maximum likelihood for the MNP model.

[^4]:    ${ }^{3}$ A detailed description of HEV model is available in Zeng (2000) and Ben-Akiva and Lerman (1985).

[^5]:    ${ }^{1} 2011$ Census

[^6]:    ${ }^{2}$ www.ametro.gr

[^7]:    ${ }^{3} 2013$ Figures, source: www.stasy.gr

[^8]:    ${ }^{4}$ Source (http://www.apergia.gr/index.php/info/statistics.html

[^9]:    ${ }^{1}$ Source: Athens Metro Development Sudy, 2008 survey, Trademco-ADO

[^10]:    * about station closure and service adjustment

[^11]:    ${ }^{1}$ We note that even, though during closures, identifying affected users is easier and Revealed Preference questionnaires can be collected, Stated Preference data plays a unique role when exploring changes in travel patterns.

[^12]:    2 The survey was administered through various websites such as www.athenstransport.com, www.apergia.gr.

[^13]:    ${ }^{1}$ http://news.kathimerini.gr/4dcgi/_w_articles_ell_1_06/09/2009_328256
    ${ }^{2}$ http://www.patt.gov.gr/main/attachments2/6500_13_02_13_dimosieusi_kdk.pdf
    ${ }^{3}$ http://www.eia.gov/forecasts/aeo/er/pdf/0383er(2013).pdf

[^14]:    ${ }^{1}$ (http://www.publicissue.gr/en/1703/bicycle-2012)

[^15]:    ${ }^{1}$ In Greece the proportion of people who telework is less than 2\% (Parent-Thirion et al. EWCS, 2005)

[^16]:    ${ }^{1}$ Calculation based on Athens public transport ticket sales of 2008

[^17]:    ${ }^{1}$ http://www.its.ucla.edu/research/EPIC/Appendix\%20A.pdf

