Using Revealed Preferences to Estimate the Value of Travel Time to Recreation Sites[1]

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Abstract

The opportunity Value of Travel Time (VTT) is one of the most important elements of the total cost of recreation day-trips and arguably the most difficult to estimate. Most studies build upon the theoretical framework proposed by Becker's (1965) by using a combination of revealed and stated preference data to estimate a value of time which is uniform in all activities and under all circumstances. This restriction is relaxed by DeSerpa's (1971) model which allows the value of saving time to be activity-specific. We present the first analysis which uses actual driving choices between open access and toll roads to estimate a VTT specific for recreation trips, thereby providing a value which conforms to both Becker's and DeSerpa's theoretical models. Using these findings we conduct a Monte Carlo simulation to identify generalizable results for subsequent valuation studies. Our results indicate that 3/4 of the wage rate provides a reasonable approximation of the average VTT for recreation trips, while the commonly implemented assumption of 1/3 of the wage rate generates downward biased results.

Key-words: value of time, value of travel time savings, recreation demand models, revealed preferences, willingness to pay space.

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1. Introduction

It is now more than a decade since Larson and Shaikh (2001) described the integration of the role of time into environmental valuation models as "one of the most challenging and important areas of recreation demand research". Recreation demand models evaluate the welfare provided by a natural resource by combining information on respondent's characteristics, site visits and travel costs, which include both "out of pocket" costs (e.g. fuel, vehicle maintenance) and the opportunity cost of travel time. Feather and Shaw (1999), among others, show that this approach produces welfare estimates that can vary up to a factor of three depending on the approach used to calculate the Value of Travel Time (VTT). On these grounds, the large volume of trips made to open-access recreational sites every year places the VTT among the key parameters for environmental and public policy evaluation (e.g. National Survey on Recreation and the Environment, 2000; Natural England, 2010). Nevertheless, a consensus on the appropriate VTT to use in recreation demand modeling is still far from being achieved (Palmquist et al., 2010). This paper contributes to the debate by developing a novel Revealed Preference (RP) method for estimating a VTT specific to leisure-related journeys by modelling route choices to open-access recreation sites. In addition, it presents a Monte Carlo simulation testing simple and generalizable VTT assumptions for future environmental valuation studies.

VTT estimates are typically based on the theoretical models describing economic decisions under limited time allocation developed by Becker (1965) and DeSerpa (1971). Becker's framework assumes fixed time and monetary prices for each good and derives a (shadow) value of time which is uniform in all activities and under all circumstances. While this result can appear questionable, it allows the VTT to be derived by analyzing any decision in which individuals trade-off money for time. For example, Stated Preference (SP) questions concerning labor market choices have been often used in the environmental valuation literature to derive the VTT for recreation demand models (e.g. Bockstael et al., 1987; Feather and Shaw, 1999; Lew and Larson, 2005).

DeSerpa's theory can be thought as a generalization of Becker's framework. While in Becker's approach both money and time costs are fixed, in DeSerpa's model only the monetary costs are set, while the amount of time devoted to each activity is allowed to vary

depending on individuals' preferences. This generalization allows the marginal utility of time (or the value of saving time) to vary among activities. Intuitively, the more an individual dislikes an activity, the higher should be her value of saving time in that specific task. While this new framework is certainly richer than Becker's original model, it has not yet been implemented in empirical recreation demand studies because of its strict data requirements. Ultimately, within DeSerpa's model, only decisions made by individuals when travelling to recreation sites can reveal their VTT for recreation. Nevertheless, estimating the VTT within a recreation demand model without including any further stated preference information (e.g. McConnell and Strand, 1981) is problematic because of the high correlation between the travel-cost and travel-time variables (e.g. Haab and McConnell, 2002; Small et al., 2005).

The main contribution of this paper is to resolve this issue by modelling the time-money trade-offs faced by individuals travelling to recreation sites when choosing between toll and free access roads, thereby providing an estimate of the VTT which is valid in both Becker's and DeSerpa's frameworks. Inferring VTT from toll road choices is particularly appealing, since saving travel time by avoiding congestions is the primary reason for the existence of toll roads and toll lanes. Indeed, using toll road decision to measure the VTT has a long history in transport economics (e.g. Bhat, 1995; Brownstone and Small, 2005; Small et al., 2005, Steimetz and Brownstone, 2005; Fosgerau et al., 2010). A recent paper by Wolff (2014) argues that this type of analyses may suffer from omitted variable bias and that modelling the relationship between vehicle speed and gasoline prices provide more robust VTT estimates. Ultimately, we believe that both approaches are valuable by having different strengths and weaknesses. While omitted variable bias is a potential concern for any applied econometric exercise, a key advantage of studying toll purchases is that they are explicitly related to time saving. In contrast, gas price is not the main variable affecting vehicle speed. The main factors are the level of traffic, the road and weather conditions, and even features which are very hard to measure such as the glare caused by the sun when it is low on the horizon (U.S. Department of Transport, 2008). Some of these impacts are difficult to account for (even by using fixed effects), without running into measurement-error problems.[4] In addition, toll

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[4] Perhaps surprisingly, the U.S. Department of Transport (2008) estimates that sun glare accounts for more than 60% of the road accidents attributable to adverse atmospheric conditions, causing every year more than three times the accidents attributable to fog, rain and snow put together. Its impact depends on a multitude of factors, such as the geometry and the orientation of the roadway and on the presence of buildings or trees blocking the sun-light. Since this effect also varies non-linearly with the time of the day and across the year, fixed-effects are not likely to be able to provide a solution but, by eliminating a lot of the variation attributable to other sources, may actually exacerbate the problem.

payment are highly visible trade-offs between time and cost, while drivers are liable to see gasoline purchases (which are necessarily in the past) as sunk costs and exhibit behaviors which do not confirm to economic rationality (Garland and Newport, 1991).

This analyses is distinguished from previous RP VTT studies by at least two additional features. First, rather than analyzing rush-hour commuters' choices on a single toll road section we consider respondents travelling from home to different recreation sites. This allows us to consider much larger time savings and longer trips. For example, the mean travel time saving in Small et al. (2005) is around 6 minutes, while our respondents, on average, can save more than one hour of travel time by using toll roads. Second, by sampling respondents directly at the visited sites, we can focus on leisure-related journeys and estimate a VTT specific to recreation. While there is considerable empirical evidence reporting significant changes in the VTT according to the purpose of the trip, the mode of travel or the level of congestion (e.g. Beesley, 1965; Makie et al., 2001; Brownstone and Small, 2005; Small et al., 2005, Fosgerau et al., 2010), to our knowledge this is the first analysis which estimates a VTT specific to recreational trips using RP data on route choices.

Our case-study sites are three beaches located on the Italian Riviera Romagnola, whose road network is a mix of toll and free access roads. Toll roads allow faster speed and can save a significant amount of travel time, particularly for long-distance trips. However, they require higher monetary costs. By re-constructing respondents' routes to the beach we indentify individuals' trade-offs and their willingness-to-pay to save time when travelling to recreation sites. In line with previous literature (e.g. Lew and Larson, 2005; Small et al, 2005) we find that individuals differ substantially in their VTT, and that both observed and un-observed heterogeneity are significant. In order to investigate the robustness of a readily generalizable, yet empirically supported, VTT for future studies, we implement a Monte Carlo simulation showing that using a fixed fraction (about 3/4) of the average wage rate generates defensible welfare estimates. Such findings also suggest that the commonly adopted strategy of assuming a VTT equal to 1/3 of the respondent's wage rate (following Cesario, 1976) produces a substantial and statistically significant downward bias in the resulting non-market benefit estimates. Results are robust in a variety of different model specifications.

The remainder of the paper is organized as follows: Section 2 summarizes DeSerpa's model and its implications for the VTT for recreation. Section 3 presents the data collection strategy

and reports descriptive statistics. Section 4 discusses the specification and estimation of the econometric models and reports the resulting VTT. Section 5 presents the results of the Monte Carlo simulation investigating the effect that different VTT definitions have on non-market benefit estimates derived via recreation demand models. Section 6 concludes.

2. DeSerpa's time allocation model and its implications for the VTT

Becker (1965) developed the first theoretical framework concerning individuals facing decisions subject to both money and time constraints. In his model the consumption of each good has fixed monetary and time costs, which allow the derivation of the shadow value of time. The subsequent generalization proposed by DeSerpa (1971) replaces the fixed time cost with time constraint inequalities, providing a more flexible and elegant framework in which the shadow value of time is replaced by a value of saving time specific to each activity.

Let x_i ($i =1,...,k$) indicate commodities or activities with associated monetary cost p_i and consumption times t_i, I the available income and T the available time (considering working time decisions as given).[5] Individuals optimize both across consumption quantities and consumption times. Their utility-maximization problem can be written as:

(1.1) $\max U(x_1,...,x_k;t_1,...,t_k)$, subject to the money and time constraints:

(1.2) $\sum_{i=1}^{k} p_i x_i = I$,

(1.3) $\sum_{i=1}^{k} t_i = T$,

(1.4) $t_i \geq a_i x_i$,   for $i = 1, ..., k$,

Equations (1.4) are time consumption inequalities in which a_i indicates the minimum amount of time necessary to consume one unit of x_i. These restrictions can be interpreted as natural and institutional constraints related to the activities' characteristics. Examples are the length of a football game, the duration of a movie, minimum travel times due to speed limits and so

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on. While these constraints place a lower bound on the amount of t_i consumed, individuals are still free to allocate more than the required time to any activity. The corresponding utility maximization problem can be represented with the following Lagrangian function:

$$(2)\ L = U(x_1,...,x_k;t_1,...,t_k) + \lambda(I - \sum_{i=1}^{k} p_i x_i) + \mu(T_0 - \sum_{i=1}^{k} t_i) + \sum_{i=1}^{k} \theta_i(t_i - a_i x_i),$$

The corresponding maximization conditions are:

$$(2.1)\ \partial L / \partial x_i = \lambda p_i + \theta_i a_i, \qquad \text{for } i = 1, ..., k,$$

$$(2.2)\ \partial L / \partial t_i = \mu - \theta_i, \qquad \text{for } i = 1, ..., k,$$

$$(2.3)\ \theta_i(t_i - a_i x_i) = 0, \qquad \text{for } i = 1, ..., k.$$

Equations (2.3) are the Kuhn-Tucker conditions corresponding to (1.4) and indicate that either $t_i = a_i x_i$ (i.e. the time allocated to the consumption of x_i is equal to the minimum amount needed and the constraint is binding) or $\theta_i = 0$ (the individual allocates to the consumption of x_i more time than it is strictly necessary).

The Lagrange multipliers λ and μ represent the marginal utility of money and the marginal utility of time. The ratio μ/λ is the shadow value of time. DeSerpa calls this quantity the "value of time as resource", which derives from the fact that time is available only in a limited amount. However, its value cannot be measured since incrementing the amount of total time available makes little sense both according to this model and in reality. Therefore, this value is not the appropriate VTT for environmental valuation. Rather, the relevant VTT corresponds to the cost associated with spending time driving rather than doing another activity which generates greater utility. This is the "value of saving time from an activity" (in our example driving) and can be calculated by dividing equation (2.2) by the marginal utility of money:

$$(3)\ \frac{\partial L_{D,SR} / \partial t_i}{\lambda} = \frac{\mu}{\lambda} - \frac{\theta_i}{\lambda}, \qquad \text{for } i = 1, ..., k.$$

This equation shows the marginal rate of substitution of t_i for money, i.e. the value of the time allocated to the consumption of x_i. DeSerpa refers to this quantity the "value of time as a commodity", which is equal to μ/λ only if $\theta_i = 0$, i.e. when an individual allocates more than the required amount of time to the consumption of x_i. On the other hand, when the time spent in consuming x_i is equivalent to the minimum required, the ratio θ_i/λ can be interpreted as the marginal value of relaxing the corresponding constrain or the "value of saving time from the activity". This notion presupposes that time can be saved and transferred to another use which generates greater utility. In addition, the value of saved time is an activity-specific quantity since it derives from the parameters θ_i. Therefore, the VTT for recreation cannot be inferred by measuring any time-money trade-offs other than those pertaining to driving decisions for recreation. As observing such trade-offs is uncommon, DeSerpa's framework has found no applications in empirical recreation demand studies so far.

Equation (3) also shows that leisure activities are among the ones in which the allocated time is higher than the minimum required. For such activities the "value of saving time" is zero as utility cannot be increased by transferring time to any other use which generates greater utility. For leisure activities $\theta_i = 0$ and the "value of time as a commodity" is equal to the "value of time as a resource". In this framework, therefore, time spent on site already has the maximum possible value and should not be included in the total cost of the trip because there is no alternative use which provides higher utility.

3. Empirical setting and data overview

Estimating a VTT for recreation consistent with DeSerpa's framework requires observations on individuals facing trade-offs involving money and driving time to recreational sites. In addition, this data needs to present relatively low correlation between travel times and travel costs, in order to obtain precise estimates of the effect of both variables on respondents' behavior. This last condition frequently fails to hold in practice. For example, recreation demand data are characterized by a very high collinearitiy between the travel-cost and travel-time variables, which significantly complicates the estimation of the VTT within standard RP travel cost models (e.g. Haab and McConnell, 2002; Small et al., 2005).

We address this correlation issue through a novel RP setting. Rather than modelling site choices as in standard recreation demand models, we analyze how individuals choose between different routes to travel to a given site, with each route option characterized by different travel times and monetary costs. The probability of person n choosing to visit site s and using route j can be written as the product of a marginal and a conditional probability as:

$$P_n(s, j) = P_n(s) \, P_n(j/s)$$

This probability can be analyzed using a nested logit model (McFadden, 1978), where the upper nest represents the beach choice and the lower nest represents the route choice. This does not necessarily imply a sequential decision process, but rather a separation of the total utility $W_n(s,j)$ in a part which is constant across routes to the same beach (which we can envisage as a function of the beach characteristics, for example), indicated with $B_n(s)$, and a part which varies with the route choice, function of travel time, monetary cost and route characteristics, which we indicate with $U_n(j)$. In formulas:

$$W_n(s, j) = B_n(s) + U_n(j) + \varepsilon_{n,j},$$

where $\varepsilon_{n,j}$ is the error term with a generalized extreme value distribution and varies over respondent and route choice.[6] Since we are interested in estimating the VTT for recreation and not in valuing the recreational sites *per se*, our focus is on the parameters in $U_n(j)$. As illustrated by Train (2009), these parameters can be consistently estimated by focusing on the lower nest, which represents the route decision choice conditional upon the beach choice, i.e. on $P_n(j/s)$.[7]

For empirical estimation, our study takes advantage of the peculiar structure of the Italian road network, which is a mixture of toll and free-access roads, providing drivers with a rich array of different options for their travel costs and times. In Italy, most high-speed highways charge access fees proportional to the length of the highway used (with little variation on a

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[6] Another error-term which varies over respondent and beach choice can be included in the model, and as long as this component is uncorrelated with $\varepsilon_{n,j}$, it can be incorporated within $B_n(s)$ without any loss of generality.

[7] Modelling the joint probability $P(s,j)$ could, in theory, increase the efficiency of the VTT estimates as also the site choice may contain information on the VTT as, for instance, individual may choose a location for the ability to get there fast. However, modelling $P(s,j)$ in our empirical framework would require an extremely large choice set, possibly including all major beaches in Italy, with several routes to reach each one of them and, therefore, is practically unfeasible.

per km basis) which are constant throughout the year and publicly available (e.g. on the site www.autostrade.it). These toll roads link all major Italian cities and can be accessed at specific stations, located roughly every 10-20 km, which connect them to the free road network. Typical toll roads consist of highways with two or three lanes in each direction, while the free-access roads have normally one or two lanes. Carpool lanes are not present in Italy. While tolls are proportional to the length of the highway used, the travel time savings can vary considerably, depending on the location of the stations relatively to the respondents' home and destination, and on the alternative routes available. This feature allows us to break-down the correlation between travel time and cost and to observe the choices of individuals facing very different time-money trade-offs.[8]

We choose as a case-study three beaches located on the Italian Riviera Romagnola: Rimini, Cesenatico and Igea-Marina. These are popular locations, attracting visitors from the entire Italian peninsula. Rimini is the most famous resort on the Riviera, and is also the most expensive, Cesenatico is slightly cheaper and visited both by families and young people, while Igea-Marina is the smallest and cheapest beach of the three and it is mainly visited by families. This diversity allows us to generate a heterogeneous sample, varying respondents' age, income and travelled distance. Furthermore, since the road network surrounding the three resorts consists of one toll highway and a variety of free access roads, the cost per minute of travel time saved is highly variable across our sample. As an illustration, Figure 1 shows possible route options for two individuals travelling to Rimini, one living in Imola (top panel) and one living in Lavezzola (bottom panel). Both panels contrast the fastest free route (FFR), indicated by the dotted line, with the fastest toll route (FTR), represented as a solid line. In both examples the FTR enters the toll road at the "Imola" access station and exits at "Rimini South" access station. This route is both faster and more expensive than the FFR (the toll between these two stations is 5€). However, the cost per unit travel time saved is very different. Travellers from Imola switching from the FFR to the FTR can save more than one hour of travel time at a cost of about 5 €/hour, while respondents from Lavezzola can only save about 20 minutes at the cost of almost 20 €/hour, which is nearly four times more expensive. Given this heterogeneity, by sampling respondents living in different locations we

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[8] Extensive toll road systems are not specific to Italy. Studies similar to ours could be implemented in other European countries, such as France, Spain and Portugal, where toll roads are fairly common. Other countries characterized by the presence of toll roads are, for example, Mexico, China, Japan, Malaysia, Pakistan and India.

are able to observe a wide range of time-cost trade-offs which allows us to obtain precise estimates of the VTT.

[Figure 1 about here]

Since the main objective of this paper is to estimate the VTT specific to recreation trips, we survey individuals directly at the three sites under study. We interviewed individuals face-to-face during the months of August and September in the years 2010 and 2011, collecting information on their trip, route choice and socio-economic characteristics. The rate of non-response was very low, with less than 5% of those approached declining to be interviewed. Restricting the analysis to respondents who face both toll and open-access route options (and hence reveal trade-offs between money and travel time) yields a sample of 457 observations, including 155 (34% of the sample) individuals travelling for short, one day, visits to the beach, and 302 (66%) respondents staying at the resorts for longer holidays, some of them lasting more than a week. This further variation also allows us to test whether different planning horizons imply different values of time.

Since respondents are unlikely to know a-priori the exact length of each alternative route and its travel cost, the relevant variables for this study are the expected travel time and cost. We assume that individuals have a feel for the distribution of the travel time and cost required by each possible route, based on their experience and on the information they can gather before the trip. This approach is standard in VTT RP studies (e.g. Brownstone and Small, 2005; Small et al., 2005, Steimetz and Brownstone, 2005). As a benchmark, we use the website maps.google.com to calculate a proxy for expected travel times. As shown in previous research, such estimates are more appropriate and reliable than using ex-post perceptions of travel time (Steimetz and Brownstone, 2005). The fuel travel costs are determined by assuming an average consumption of 1 litre per 18 km and the average fuel price in summer 2010 (1.29 €/litre) and 2011 (1.53 €/litre) as provided by the Department of Economic Development (http://dgerm.sviluppoeconomico.gov.it).

Since the number of possible routes connecting two points on a road network is, at least in theory, infinite, we use some simple rules to indentify meaningful routes and thereby determine appropriate choice-sets for each respondent. A "core" choice-set for each respondent is defined by the following options: the FFR; the FTR; the FT1A (the fastest route

accessing the toll road one station after that used in the FTR); the FT1B (the fastest route exiting the toll road one station before the one in the FTR). These last two choices are relevant if the respondent's house or the beach is located in-between toll road stations, and entering/exiting the highway at the next/earlier station provides better time-money trade-off than either the FFR or the FTR. We finally include in each respondent's choice-set all the alternative routes chosen by individuals travelling from the same "outset area". These outset areas are defined in terms of toll road use in order to group together individuals with the same entrance and exit according to the FTR (irrespective of whether or not they choose to use the toll road). Only 25% of the respondents belong to areas in which routes other than FFR, FTR, FT1A and FT1B are chosen.

[Table 1 about here]

Routes' descriptive statistics

Descriptive statistics for the route options are reported in Table 1. For most people (56%), the FTR is the preferred route, followed by the FFR (15%). Only 11% of the respondents choose a route outside the 4 options included in the "core" choice set. The variability in travel times is substantial. Considering the FTR, for example, travel times ranges from less than 30 minutes to more than 8 hours. Considering monetary costs, a significant fraction is made up by toll fees. For instance, choosing the FTR instead of the FFR increases average travel costs by 40%. Columns 7 to 9 of Table 1 report the descriptive statistics of additional route characteristics which could influence respondents' route choices. These are represented via dummy variables which are respectively equal to one if the route includes a fast bypass road, a one-lane mountain road, and a scenic costal road. Non-toll bypass road are normally two lane roads which allow a relatively higher driving speed compared to the standard one-lane roads characterizing the free access Italian road network. However, during peak hours they can become rapidly congested and cause considerable delays. Therefore their effect on route choice could vary with the general conditions of the road network. Single lane mountain routes (in our sample this includes those crossing the Appenini mountain range) are typically narrow and winding and hence potentially challenging and time-consuming. Such characteristics may negatively affect the choice probability of such roads. Finally, routes including scenic ocean vistas may reduce the dis-utility of driving or even provide positive utility. We define the latter routes as those which include sections less than 200m from the sea. However, only a very small fraction of our respondents (7%) have routes with this

characteristic in their choice-set and, therefore, we may not be able to estimate this last effect precisely.

To illustrate the different time-money trade-offs faced by the individuals in our sample, we calculate the cost per hour of travel time saved comparing the two most frequently chosen routes: FTR and FRR. For descriptive purposes, this ratio can be approximated by dividing the toll by the difference in travel times, since fuel costs are typically very similar between the two options. The distribution of the toll cost per hour of time saved is represented by the histogram illustrated in Figure 2. While most individuals face toll costs between €5 and €10/hour, there is considerable variability in trade-offs, with a significant proportion of respondents facing very high potential fees, rising to more than €50/hour.

[Figure 2 about here]

Descriptive statistics for all the other variables included in the study are reported in Table 2. Driver's income, age and the number of passengers show great heterogeneity although most drivers are male (71%) and most passengers are older than 16, with an average of 2.3 adults per party. By using the common assumption of 2000 work hours per year (e.g. Haab and McConnell, 2002; Hynes et al., 2009), we calculate respondents' average gross hourly wage rate as being about €12/hour. This corresponds to a monthly income of about €2100, which is similar to the average level of €2054 reported by the Italian Statistical Institute (Istat, http://dati.istat.it/?lang=en) for the year 2011. Our sample, therefore, represents well the average income of the entire country. Finally, the last three columns compare respondents across route-choices, showing that our sample is essentially well balanced in that the average values of the socio-economic characteristics are basically the same for individuals choosing either FTR, FFR or any other route.

[Table 2 about here]

Respondents' descriptive statistics

4. The econometric model

4.1 The empirical specification

As illustrated in the previous section, we estimate the VTT by focusing on the route choice as conditional on the recreation site choice. Assuming that utility is linear in income and, for simplicity, eliminating that portion of utility which is constant among route alternatives, $B_n(s)$, we can write the (dis-) utility which person n ($n=1,..., N$) receives from choosing route j ($j=1,..., J$) as:

(4) $U_n(j) = U_{n,j} = \lambda_n c_{n,j} + \theta_n t_{n,j} + q_j + \varepsilon_{n,j}$,

where $t_{n,j}$ is the route time, $c_{n,j}$ is the route cost (including both toll and fuel cost, which we assume are equally shared among all adults in the car), θ_n is the marginal (dis-) utility of spending time driving rather than in other activities which generate greater utility and λ_n is the marginal utility of money. Both coefficients correspond to the parameters of DeSerpa's model reported in equation (2), and are allowed to vary across respondents. Furthermore, q_j includes all observed characteristics of the route which have some implications for the choice and the residual term $\varepsilon_{n,j}$ encompasses the unobserved characteristics of both the respondent and the route. This residual component is assumed to be distributed as a type I extreme value with scale parameter k_n. Respondent n chooses route j if $U_{n,j} > U_{n,i} \ \forall i$. Finally, the parameter of travel time, while allowed to differ across respondents, does not vary per route option. Therefore, while we encompass route characteristics through the term q_j, we also assume that driving produces the same (dis-) utility per unit of time regardless of the type of road travelled.[9]

As shown in equation (3), in this model the relevant VTT for recreation is the ratio of the marginal (dis-)utility of time spent driving to the marginal utility of money:

(5) $VTT_n = \dfrac{\partial U_{n,j} / \partial t_{n,j}}{\partial U_{n,j} / \partial c_{n,j}} = \dfrac{\theta_n}{\lambda_n}$.

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[9] In line with most RP analyses we do not consider the effect of possible road congestion, which is commonly referred to as the "travel time reliability" and typically investigated using SP data (e.g. Li et al., 2010) or by combining RP and SP information (e.g. Small et al., 2005). However, congested roads are not likely to be an issue for our estimates, since most of the respondents (around 90%) did not report any significant road traffic. In addition, only a small fraction of the interviewees who actually encountered road congestion adjusted their route accordingly, typically abandoning congested highway for smaller roads. We eliminated these individuals (about 1% of the sample) from the analysis since their travelled route differed from the one they had planned *a priori* based on expected travel cost and travel time.

As dividing or multiplying utility does not affect behavior, we can divide (4) by the scale parameter obtaining an error term with the same variance for all respondents:

$$(6) \quad U_{n,j} = \frac{\lambda_n}{k_n} c_{n,j} + \frac{\theta_n}{k_n} t_{n,j} + \frac{q_j}{k_n} + \omega_{n,j} \ .$$

Train and Weeks (2005) refer to this equation as a model specified in "preference space". Unobserved heterogeneity in preferences can be encompassed by specifying a probability distribution for the time and cost coefficients and estimating the model as a mixed logit (e.g. Train, 1998, 2009). Among the most commonly applied distributions are the normal, the log-normal, the uniform and the triangular. However, recent work has shown that models with preference parameters distributed according to these simple probability densities generate Willingness to Pay (WTP) distributions (in our case VTT distributions) with counter-intuitive features, such as excessively long tails or non-finite moments (e.g. Scarpa et al., 2008). A possible solution is to define a cost coefficient which is constant across respondents (e.g. Revelt and Train, 1998). This assumption allows the WTP distribution to match that of the time coefficient. However, this restriction is somehow counter-intuitive since, as shown in equation (6), a fixed cost coefficient ($\lambda_n = \lambda$, $\forall n$) implies that the standard deviation of the residual term $\varepsilon_{j,n}$ is the same for all respondents ($k_n = k$, $\forall n$). If violated, this latter assumption will induce biased inference by erroneously attributing variation in scale to variation in WTP.

Train and Weeks (2005) resolve this issue by re-writing the model in what they define as being the WTP representation, which, in our context, we refer to as VTT space. Defining $\lambda_n{}^* = \lambda_n / k_n$ and $q_{n,j}{}^* = q_j / \lambda_n$, we can re-write (6) as:

$$(7) \quad U_{n,j} = \lambda_n^* [c_{n,j} + VTT_n t_{n,j} + q_{n,j}^*] + \omega_{n,j} \ .$$

In this parameterization the variation in VTT is independent from the variation in scale, which is encompassed in the cost coefficient λ_n^*. Another advantage of this approach is that we can directly specify a distribution for the VTT rather than generating it numerically as a ratio. In addition, we can include some observed factors within the specification of the VTT (e.g. $VTT_n = \alpha_{0,n} + \alpha_1 inc_n$, with inc_n = income of respondent n) and directly test their

significance with standard inference (e.g. Thiene and Scarpa, 2009). The appeal of the "WTP space" parameterization over the traditional "preference space" specification for VTT estimates is confirmed by Hensher and Greene (2011), among others.

Model (7) is a non-linear in parameters mixed logit model and its estimation can be implemented via Simulated Maximum Likelihood (SML) (Train, 2009, Scarpa et al., 2008). Conditional on the values of the random parameters $\gamma_n = \{\lambda_n, VTT_n\}$, the probability of person n choosing route j can be written as the standard logit formula (McFadden, 1974):

$$(8)\ p_n(j \mid \gamma_n) = \frac{\exp(V_{n,j})}{\sum_{i=1}^{J} \exp(V_{n,i})},$$

where $V_{n,i} = U_{n,i} - \omega_{n,i}$. The unconditional probability is given by the integral of (8) over all possible values of γ_n, weighted by their density:

$$p_n(j) = \int p_n(j \mid \gamma_n) g(\gamma_n) d\gamma_n,$$

where $g(.)$ is the joint probability distribution function of the random parameters. Indicating with y_n the dummy variable identifying the route chosen by respondent n, the log-likelihood function to be maximized is:

$$(9)\ \ln L = \sum_{n=1}^{N} p_n(j) y_n.$$

Rather than directly maximizing the likelihood (9), we approximate the integral over γ_n via simulation. This approach consists of taking draws from the distribution of the random parameters, calculating $p_n(j)$ for every draw and then averaging the results. This SML estimator is consistent, asymptotically normal and efficient for an increasing number of draws (Train, 2009). Estimation is implemented in the free software R (R development core team, 2008) using the Nelder-Mead (1965) maximization algorithm and 50 Halton draws per person (as per Train, 2009). The R code and the data used in this study are available on the corresponding Author webpage.

4.2 Estimation results

The results provided by different model specifications are reported in Table 3. As a benchmark, the first column reports a standard conditional logit model in preference space with only route time and cost as choice attributes (Model A1). The estimated VTT is about €8.6/hour which corresponds to roughly 70% of the average wage rate. This is close to the value reported by Steimetz and Brownstone (2005) for non-work related trips ($11/hour). For illustrative purposes, Model A2 in the second column reports the re-parameterization of Model A1 in VTT space. Since the two models do not include any random parameters, they yield exactly the same VTT estimate and log-likelihood. All the other models in Table 3 are estimated directly in VTT space. Model B, reported in the third column, extends the base specification by including route characteristics. The coefficients show that, given the same cost and time, the fastest free route (FFR) and the fastest toll route (FTR) are much more likely to be chosen than those other routes containing different combinations of toll and free roads. This reflects the fact that FFR and FTR are the two most cognitively straightforward routes and those which, for example, can be automatically selected on standard satellite navigators. In contrast, alternative routes, such as FT1A or FT1B, require greater knowledge of the area and its road network. In addition, routes including tracts of bypass roads are more likely to be chosen than other routes. Since bypasses are typically congested in peak hours but offer fast driving options during off-peak, this result suggests that the recreational trips in our sample are typically carried out outside peak time. As expected, one lane mountain routes are considerably less likely to be chosen than other routes because of their difficult driving conditions. Finally, the dummy variable identifying scenic costal routes is not significantly different from zero (although this result might reflect the low number of respondents with such options within their choice sets).

[Table 3 about here]

Model estimates and corresponding VTT

Model C includes both route and respondent characteristics. In line with our expectations and consistent with the results of previous work (e.g. Deacon and Sonstelie, 1985; Steimetz and Brownstone, 2005; Small et al, 2005), income has a positive effect. With every additional €10,000 of gross yearly salary the VTT increases, on average, by €0.9 per hour. In addition, the VTT of respondents older than 60 years is, on average, about 30% lower

than that of younger age groups. This finding can be explained by the high proportion of retired workers in this age class who, by having more free time, may also present a lower VTT. Finally, our estimates indicate that neither the gender of the driver nor the length of holiday have any significant influence on the value of saving travel time.[10]

Models D and E relax the constant scale parameter assumption and introduce un-observed taste heterogeneity. In Model D both the cost and the VTT parameters are assumed to be normally distributed and in Model E they are assumed to follow a triangular distribution in order to restrict the effect of increases in costs and travel time to always having a negative effect on utility.[11] The results of the normally distributed random effects model (Model D) confirm findings in the literature (e.g. Lew and Larson, 2005) in showing significant un-observed heterogeneity, with both random parameters standard errors being highly statistically significant. Considering an interval equal to plus and minus one standard error, the VTT for recreation varies from about €7.7/hour to €11.5/hour, with an average of €9.4/hour. Also the triangular specification (Model E) provides a better fit than the fixed effect one (Model C), while having the same number of parameters. This model estimates the average VTT to be around €9.2/hour.

Overall, starting from a base model with only time and monetary cost parameters and, in sequence, including routes' characteristics, respondents' characteristics and un-observed heterogeneity considerably improves the model fit (the pseudo R^2 more than doubles going from 0.13 to 0.27) but does not significantly change our findings. In fact, our VTT estimates are remarkably stable, remaining between €8.4/hour and €9.4/hour, or around 70-80% of the wage rate across all specifications. As introducing both observed and un-observed heterogeneity does not significantly affect the VTT parameter, any potential bias arising from possible omitted variables should also not be of strong concern for our results. In addition, although our study focuses on the VTT for recreation, our empirical estimates fall within the lower end of the range reported by previous RP studies on the VTT for generic road trips (e.g. Deacon and Sonstelie, 1985, and Small et al., 2005, respectively report a VTT of about 80% and 93% of the wage rate). Overall, this results aligns our findings with the earlier literature,

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[10] We also tested if VTT changes with the length of the trip, by allowing the time parameter to change for short (FTR time ≤ 60 min), medium (60 min < FTR time ≤ 150 min) and long (FTR time > 150 min) trips. These additional parameters were not statistically significant.

[11] Another approach to implement this restriction is to assume a log-normal distribution. However, similarly to others (e.g. Small et al., 2005), we were unable to obtain convergence with that specification.

as both intuition and prior research (e.g. Steimetz and Brownstone, 2005) indicate that non-work related trips should present a (slightly) lower VTT than business-related ones. This feature provides supporting evidence on the ability of our estimates to represent other countries and contexts.

Finally, while income is a significant factor in explaining the VTT, we also find strong unobserved heterogeneity, with estimated person-specific VTTs ranging from less than 50% to more than 100% of the personal wage depending on respondents' tastes and attitudes towards driving. Therefore, our findings agree with those of Lew and Larson (2005) and Small et al. (2005), which show that both observed and un-observed sources of heterogeneity are important in VTT elicitation. The next section analyzes which assumptions can be implemented in empirical studies in which VTT estimation is not feasible. To do so, we undertake a simple Monte Carlo simulation comparing some of the options which have been implemented so far in the recreation demand modeling literature.

5. Testing alternative VTT assumptions in recreation demand studies: a Monte Carlo simulation

Previous studies (e.g. McKean et al., 1995; Feather and Shaw, 1999) show that welfare estimates derived via recreation demand models are highly sensitive to the assumed VTT. While our analysis employs a rich dataset on route options, it is not always possible to estimate person-specific VTTs within every recreation demand study. When this estimation is unfeasible, which is the appropriate VTT to use? In order to answer this question, we design a simple Monte Carlo simulation based on our data and estimates. We proceed in two steps. First, we generate site-visits using the person-specific VTT predicted by our best fitting model, which includes both observed and un-observed heterogeneity. This produces the typical data that a recreational survey would collect. Second, we estimate competing recreation demand models employing different VTT assumptions and contrast them with the "true" model based on the un-observed, person-specific VTT used to generate the data. Comparing welfare estimates across models allow us to draw some guidelines for applied recreation demand research.

For simplicity, and in order to simulate one of the most common valuation frameworks, we follow McKean et al. (1995) in focusing our simulation on a single-site model. We choose the beach of Cesenatico, for which we have 247 survey respondents. For each individual in this sub-sample, we calculate the VTT according to Model D in Table 3, which encompasses both observed and un-observed heterogeneity with normally distributed random parameters. We estimate person-specific parameters following the approach outlined by Train (2009). Specifically, we derive the distribution of the VTT for each respondent as conditional to the data by using the Bayes' rule:

$$(10)\ h(VTT_n \mid j, z_n) = \frac{p_n\left(j \mid z_n, VTT_n\right) N(VTT_n \mid \Omega)}{p_n\left(j \mid z_n, \Omega\right)},$$

where VTT_n is the value of travel time for respondent n, j indicates the chosen option, z_n represents all the explanatory variables in the model (i.e. income, age, and gender and route characteristics) and Ω are the parameter estimates, including the mean and standard error of the random parameters. The function $h(.)$ is the distribution of VTT_n given the observables, $N(.)$ is the Gaussian probability distribution of VTT_n given the parameters, $p_n (j \mid z_n, VTT_n)$ is the probability of the observed choice given the value of time and the explanatory variables, and $p_n (j \mid z_n, \Omega)$ is the integral of $p_n (j \mid z_n, VTT_n)$ on the parameter space. This denominator is a constant and, therefore, $h(.)$ is proportional to the numerator. As suggested by Train (2009), we calculate the expected value of $h(.)$ by simulation, randomly generating 1000 draws of VTT_n from the normal population density $N(VTT_n \mid \Omega)$ and computing their weighted mean, with weights proportional to $p_n (j \mid z_n, VTT_n)$.

After calculating individual-specific VTTs, we generate, for each respondent, the number of visits (R_n) to Cesenatico beach using a simple trip-simulation function specified with the following exponential form:

$$(11)\ R_n = \exp(\beta_0 - \beta_1 TC_n + u_n),$$

with TC_n = total round-trip cost from the respondent's home to the beach (including both fuel cost and VTT_n and considering the least-cost route), u_n = i.i.d. Gaussian residual term, and β_0 and β_1 functional form parameters. This Data Generating Process (DGP) simulates the

information that a standard single-site recreation survey would collect (e.g. McKean et al., 1995; Haab and McConnell, 2002).

We can now estimate simple models explaining the simulated visits as a function of the total round-trip cost, which we calculate by using different VTT definitions in order to assess their impacts on WTP estimates. We maintain the exponential form used in the DGP and estimate the following model:

$$(12)\, \ln(R_n) = b_0 - b_1 TC_n^* + \varepsilon_n,$$

where the TC_n^* is the round-trip cost which we compute considering the following VTT definitions: (*a*) the "true" person-specific value used in the DGP (i.e. $TC_n^* = TC_n$), (*b*) zero, (*c*) 1/3 of the respondent wage rate (Cesario, 1976), (*d*) the respondent full wage rate, (e) 3/4 (or 75%) of the respondent wage rate and (*f*) 3/4 of the average wage rate. The last two definitions use the average fraction of the salary estimated on our data but differ in that for option (*e*) the VTT is proportional to each person's salary while option (*f*) uses a "one size fits all" approach by assigning the same VTT to all respondents, including those who are currently un-employed.

As consumer surplus we use the WTP of access as given by Haab and McConnell (2002):

$$(13)\, WTP = \int_{TC_n^*}^{\infty} \exp(\hat{b}_0 + \hat{b}_1 c)\, dc = -\frac{y_n}{\hat{b}_1},$$

where the "hat" indicates the parameter estimates of (12) obtained via ordinary least squares and all other symbols are defined as previously.

We simulate several demand equations varying the intercept (b_0) and slope (b_1) and the standard error of the trip-generation function to compare VTT assumptions in different settings. Since findings remained consistent across all specifications, for ease of exposition we report only the results obtained using "average" parameter values within the explored DGP space, i.e. setting $b_0 = 4$, $b_1 = 0.5$ and s.e.(u_n) = 0.5 in equation (11). These values generate a number of trips per respondent varying from almost 0 to around 100.

[Table 4 about here]

Monte Carlo simulation: welfare estimates using different VTT

Results obtained from 5000 Monte Carlo repetitions comparing WTP estimates using our six different VTT definitions are presented in Table 4 and in the box-plots in Figure 3. In line with previous literature, WTP estimates vary considerably depending on how the VTT is determined. The first row/box-plot reports the WTP estimates obtained by using the "true" un-observed person-specific VTT used to generate the data. The mean WTP is around €9.3, but there is considerable variability between respondents, with the 5th percentile being only €0.6 and the 95th almost €11.5. The second row reports the estimates obtained by assuming that travel time has no value. As expected, this definition generates a significantly lower consumer surplus, roughly reducing the average WTP of a factor of three to about €2.9. As shown in the third row, the common assumption that VTT is equal to 1/3 of the wage rate (as per Cesario, 1976, and in numerous other studies) also produces downwardly biased estimates, with an average of about €7.2. On the other hand, the results presented in the fourth row show that assuming that the VTT is equal to the full wage substantially inflates WTP values, the average being about €12, which is higher than the 95th percentile calculated from the "true" VTT.

[Figure 3 about here]

The best approximation of the true WTP is provided by adopting the assumption that VTT is 3/4 of the wage rate, reported in the last two rows of Table 4, with means and percentiles only slightly higher than the ones used to in the DGP. As shown by comparing the box-plots in Figure 3, these are the only assumptions which produce 95% confidence intervals which include the mean of the WTP calculated using the true VTT value. In addition, despite salary being a significant factor in the simulation of the person-specific VTT data, assuming the VTT to be 3/4 of average wage rate produces slightly better estimates than defining the VTT equal to 3/4 of the personal wage rate. This may look like a surprising result, but it can be explained by the strong importance that un-observed factors, such as attitudes towards driving, play in determining the VTT. As these factors cannot be observed and do not necessarily vary proportionally with income, using a "one size fits all" approach by approximating the true VTT with a value which is a fraction of the average salary can be a

simple and yet effective strategy for obtaining sensible WTP estimates for valuing recreational sites. Another advantage of this approach is that it provides VTT estimates for both employed and unemployed respondents, rather than implicitly assuming that those outside the workforce have zero VTT as in conventional analyses. As shown by Feather and Shaw (1999), among others, this latter approach can downwardly bias WTP values significantly if a large proportion of respondents are unemployed. Obviously, assuming the same VTT for all respondents still remains a second-best strategy, which should be implemented only when investigating individual-specific VTTs is not a feasible option.

6. Conclusions and further research

We introduce a novel RP setting to estimate the VTT for recreation trips based on travelling choices between alternative routes characterized by different time and monetary costs. Compared with previous studies, which use labor market choices (e.g. Feather and Shaw, 1999; Lew and Larson, 2005) or household maintenance options (Palmquist et al., 2010) to estimate the value of time, our analysis has the important advantage of being based on actual travel-choice decisions for recreation. Therefore, it provides a VTT which is appropriate in both Becker's (1965) model of economic decisions with time constraints and in the subsequent generalization by DeSerpa's (1971), while earlier analyses are valid only within the first and more restrictive framework.

The average VTT of our sample is between €8.4/hour and €9.4/hour, or around 3/4 of the average wage rate; a value which is in the lower end of the range identified by previous RP studies on the VTT of generic road trips, reassuring us on the external validity of our results. In addition, our estimates confirm previous findings (e.g. Lew and Larson, 2005) in that individuals differ substantially in how they value travel time to recreational sites, and that both observed and un-observed characteristics are important in determining that value. For instance, VTT increases with income and decreases for those who are older than 60 years, probably reflecting the higher proportion of retired people with fewer commitments in this age group. As our results remain robust in a variety of model specifications (including both observed and un-observed heterogeneity), arguably any potential bias arising from possible omitted variables should also not be of strong concern for our estimates.

As shown in previous studies (e.g. Feather and Shaw, 1999), welfare estimates from recreation demand models are highly sensitive to the assumed VTT. Earlier work (e.g. Lew and Larson, 2005; Palmquist et al., 2010) included SP questions on labor market or household maintenance decisions within the standard RP recreation survey to recover individual-specific VTTs for recreation. Another feasible option could be to add SP choices on alternative routes to reach the recreation sites providing respondents with different money-travel time trade-offs. However, further research is necessary to test if values provided by this SP approach conform to RP estimates, since findings to date seem to indicate a significant gap between SP and RP estimates of VTT (e.g. Brownstone and Small, 2005; Small et al., 2005).

Finally, our Monte Carlo simulation shows which simple assumptions can be implemented in applied recreation demand models when it is not feasible to estimate person-specific VTT measures. Assuming VTTs which are either zero or 1/3 of the wage rate (as suggested by Cesario, 1976, and implemented in many subsequent studies) clearly produces downward biased estimates, while defining the VTT to be equal to the full wage rate somewhat overestimates values. In our case-study we find that ignoring respondent heterogeneity and setting VTT equal to 3/4 of the average wage in the sample provides defensible results which, on average, are not significantly different from those obtained using the "true", un-observed, VTT used to generate the data.

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Tables and Figures

Table 1

Routes' descriptive statistics

Route	Time (minutes)			Fuel cost(€)	Toll cost(€)	Include bypass	Include mountain road	Include scenic road	% chosen
	mean	min	max	mean	mean	mean	mean	mean	
FTR	137.8	28.0	495.0	16.22	11.26	0.09	0.02	0.00	56
FFR	233.9	35.0	763.0	15.49	0.00	0.16	0.09	0.07	15
FT1A	148.7	37.0	498.0	16.35	10.29	0.17	0.02	0.00	14
FT1B	144.7	35.0	502.0	16.32	10.76	0.09	0.02	0.00	4
other routes	174.2	84	418.0	17.25	9.35	0.25	0.01	0.00	11

Notes: total number of observations equal to 457. The statistics of the "other routes" category refers only to those respondents who has these options within their choice-set it (25% of the sample), whereas the other statistics refer to the full sample. FTR the fastest tolls route, FFR the fastest free route, FT1A the fastest toll route by accessing the toll road one station after the one in FTR and FT1B the fastest route by exiting the toll road one station before the one in FTR. Cost deflated to year 2010 by using gross domestic product deflator (source: World Bank, www.worldbank.org).

Table 2

Respondents' descriptive statistics

	$\bar{x}$	$\hat{s}(x)$	min	max	$\bar{x}$ (y=FTR)	$\bar{x}$ (y=FFR)	$\bar{x}$ (y=other)
Personal income (1000€/month)	2.11	1.33	0.25	11.20	2.15	2.33	1.92
age (years)	40.70	12.17	18.00	76.00	40.00	43.38	40.51
Gender	0.29	0.45	0	1	0.30	0.29	0.26
people in the car	2.85	1.13	1	7	2.89	2.54	2.92
> 16 years old	2.27	0.86	1	7	2.32	2.07	2.27
< 16 years old	0.59	0.84	0	4	0.57	0.47	0.65

Notes: $\bar{x}$ *indicates the sample mean,* $\hat{s}(x)$ *the sample standard deviation. The y=FTR/FFT/other indicates the subsample of respondents who choose respectively the fastest tool route (n=256), the fastest free route (n=69), all other routes (n=133). The statistics on age and income (before tax) refer to the driver. Income deflated to year 2010 by using gross domestic product deflator (source: World Bank,* www.worldbank.org*).*

Table 3

Model estimates and corresponding VTT

|	Preference space		VTT space			
	Model A1 *Base model*	Model A2 *Base model*	Model B *route characteristics*	Model C *route & respondent characteristics*	Model D *unobserved heterogeneity (Gaussian)*	Model E *unobserved heterogeneity (Triangular)*
time	-3.031 ***	0.858***	0.835***	0.700***	0.777***	0.712***
	(0.361)	(0.072)	(0.107)	(0.136)	(0.121)	(0.122)
s.e.(time)					0.218***	
					(0.051)	
Cost	-3.533***	-3.533***	-2.996***	-3.116***	-6.626***	-6.166***
	(0.543)	(0.543)	(0.549)	(0.562)	(1.461)	(1.263)
s.e.(cost)					3.396***	
					(0.888)	
FTR			-0.425***	-0.394***	-0.166***	-0.175***
			(0.089)	(0.083)	(0.047)	(0.047)
FFR			-0.416***	-0.440***	-0.263***	-0.262***
			(0.110)	(0.113)	(0.073)	(0.073)
Bypass			-0.243*	-0.234**	-0.151***	-0.153***
			(0.144)	(0.112)	(0.063)	(0.065)
Scenary			0.218	0.225	0.153	0.232
			(0.266)	(0.211)	(0.171)	(0.171)
Mountain			0.612***	0.629***	0.549***	0.537***
			(0.233)	(0.221)	(0.187)	(0.188)
*Time * gender*				0.039	0.016	0.052
				(0.108)	(0.093)	(0.088)
*Time * d_age ≥ 60*				-0.305***	-0.321***	-0.302***
				(0.119)	(0.107)	(0.119)
*Time * p_inc*				0.091*	0.085*	0.092**
				(0.053)	(0.048)	(0.036)
*Time * one_day*				0.138	-0.003	0.054
				(0.141)	(0.106)	(0.107)
Log-likelihood	-580.06	-580.06	-500.31	-492.83	-483.33	-485.98
Pseudo R^2	0.13	0.13	0.25	0.26	0.28	0.27
Mean WTP (€/hour)	8.58	8.58	8.35	9.26	9.35	9.16

Notes: travel cost expressed in 10€ (e.g. 100€ = 10), travel time in hours, gross income in 1000€/year (e.g. 20,000€/year = 20). * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level.

Table 4

Monte Carlo simulation: welfare estimates using different VTT

|	Mean WTP (€)	5% quantile of WTP (€)	95% quantile of WTP(€)
true VTT$_n$	9.29 *(8.61, 10.10)*	0.57 *(0.47, 0.71)*	11.47 *(10.26, 12.83)*
VTT$_n$ = 0	2.88 *(2.67, 3.13)*	0.18 *(0.14, 0.22)*	3.56 *(3.18, 3.99)*
VTT$_n$ = 1/3w$_n$	7.21 *(6.68, 7.85)*	0.44 *(0.36, 0.54)*	8.91 *(7.9, 9.98)*
VTT$_n$ = w$_n$	11.99 *(11.11, 13.05)*	0.74 *(0.60, 0.92)*	14.81 *(13.25, 16.59)*
VTT$_n$ = 3/4 w$_n$	10.03 *(9.28, 10.04)*	0.61 *(0.50, 0.76)*	12.39 *(11.07, 13.89)*
VTT$_n$ = 3/4 $\overline{w}$	9.78 *(9.06, 10.64)*	0.60 *(0.45, 0.74)*	12.06 *(10.82, 13.52)*

Notes: results generated with 5000 Monte Carlo repetition, w_n indicates the person specific wage rate and $\overline{\overline{w}}$ indicates the sample mean wage rate. In brackets the 95% confidence intervals.

Figure 1: Possible routes and cost per time saved for two individuals living in different cities
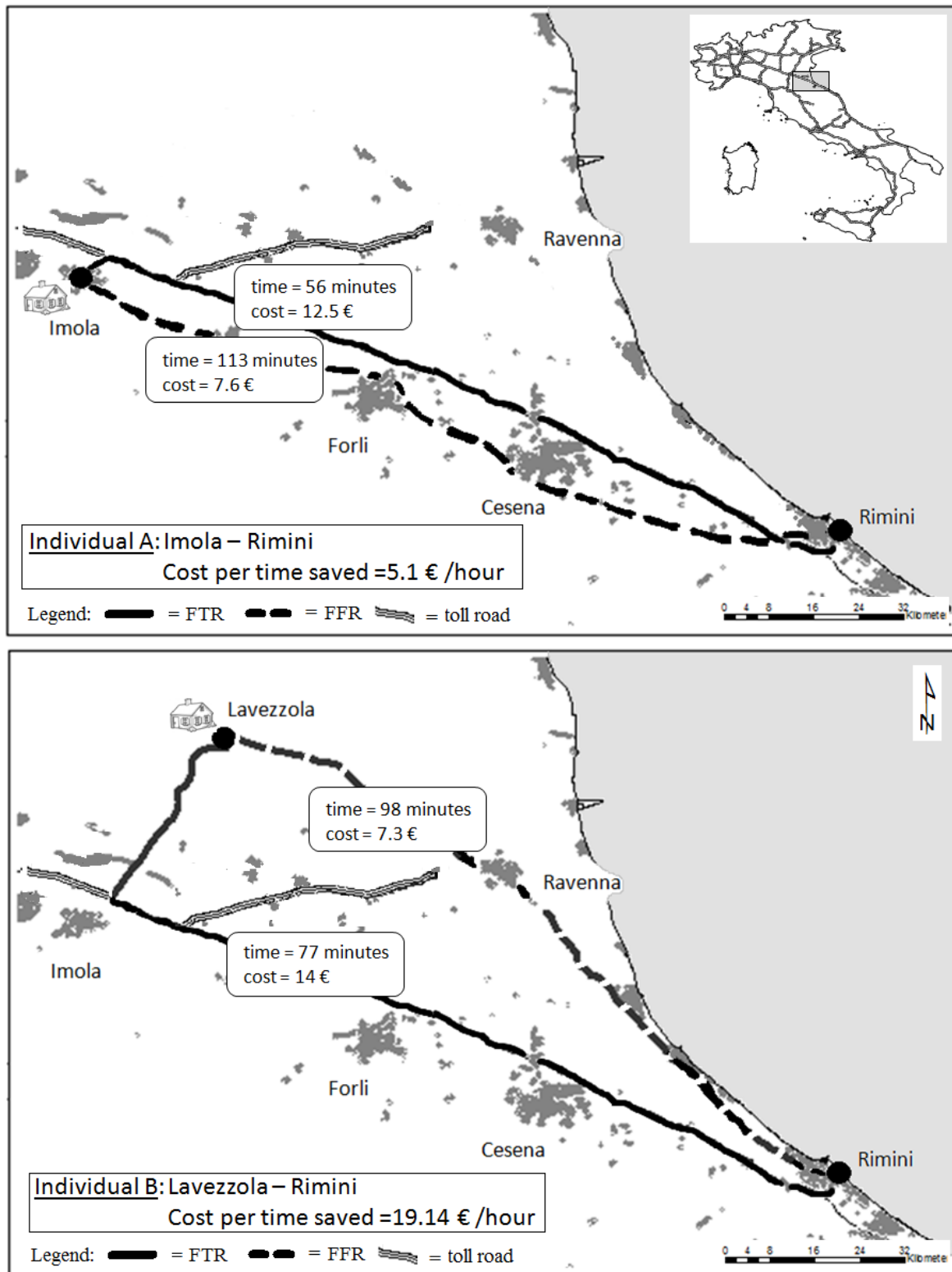
Notes: The small inset map at the top represents the toll highway network in Italy. The upper panel shows two possible routes for a person living in Imola and travelling to Rimini, with the dotted line representing the fastest free route (FFR) and the solid line indicating the fastest route including a toll road (FTR). The lower panel represent the same route options for a person living in Lavezzola. Travel times calculated via the web site maps.google.com, fuel cost computed using the average fuel price in summer 2010 (1.29€/litre). The toll cost is €5.

Figure 2: Histogram of toll cost per hour of travel time saved
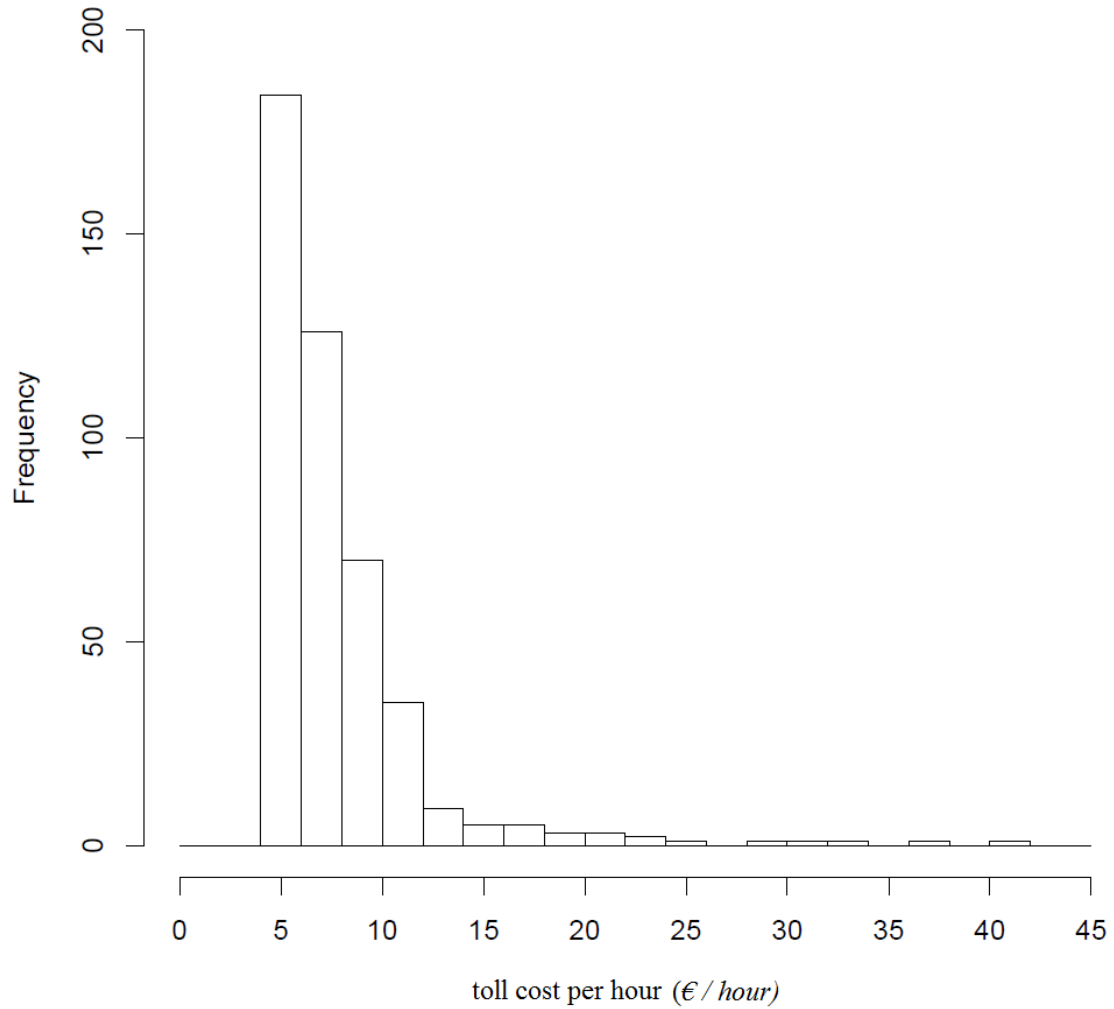
Notes: histogram of the toll cost per hour of travel time saved, which is defined as the ratio between (a) the toll and (b) the difference in time between the fastest toll route and the fastest free route for our sample (N=457). Note that 9 respondents have a toll-time ratio higher than 50€/hour and lie outside the range of the plotted values.

Figure 3: average WTP estimates
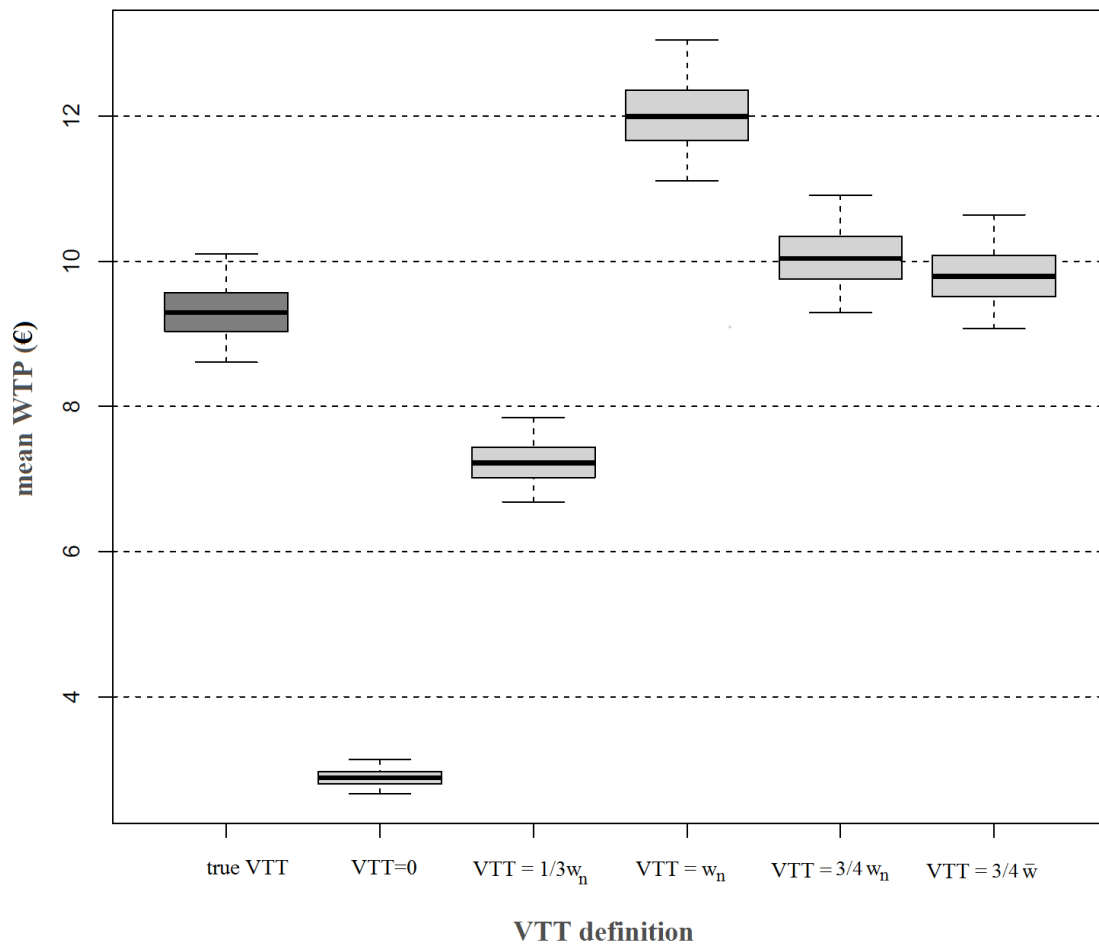
Notes: Confidence intervals for the mean WTP of access, calculated with 5000 bootstrap repetitions. The gray box indicates the 1st and 3rd quartile, the wishers the 95% confidence interval. The symbol w_n indicates the person specific wage rate and $\overline{\overline{w}}$ indicates the sample mean wage rate.