

Who is Willing to Pay for Travel Time Savings and How Much? An Iterative Bidding Contingent Valuation Study in Mumbai

Dale Robbennolt

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Email: dar4836@utexas.edu

Hyunjun Hwang

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Email: hjhwang@utexas.edu

Aishwarya Jaiswal

Indian Institute of Management Ahmedabad
Centre for Transportation and Logistics
Forum Tower, F-07 R-01, Vastrapur, Ahmedabad, Gujarat 380015, India
Email: aishwaryaj@iima.ac.in

Sagar Verma

Indian Institute of Management Ahmedabad
Public Systems Group
Forum Tower, F-07 R-01, Vastrapur, Ahmedabad, Gujarat 380015, India
Email: phd22sagarv@iima.ac.in

Sandip Chakrabarti

Indian Institute of Management Ahmedabad
Public Systems Group
Forum Tower, F-07 R-01, Vastrapur, Ahmedabad, Gujarat 380015, India
Email: sandipc@iima.ac.in

Chandra Bhat (corresponding author)

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Email: bhat@mail.utexas.edu

ABSTRACT

The value of travel time savings is one of the most widely used concepts in the transportation sector, serving as a critical component of transportation project evaluation, policy formulation, and transportation investment decisions. In this paper, we examine the value of travel time savings as measured using an iterative bidding contingent valuation approach in the context of Mumbai, India. By directly measuring the value of travel time savings, rather than imputing it, we are able to efficiently consider variations across individual characteristics and trip contexts. As importantly, we account for the possibility that some individuals may not be willing to pay at all for travel time savings, jointly modeling a binary outcome representing whether an individual is willing to pay at all (WTP) alongside the continuous value of travel time savings among those who are willing to pay. This approach allows us to identify those individuals who have a value of travel time savings (VTTS) of zero, which may occur due to very different psychological reasons than simply having a low value of travel time savings. The findings reveal significant differences in WTP and VTTS across population subgroups and trip characteristics. The results have important implications for the evaluation of transportation policies, prioritization of transportation infrastructure improvements, and development of priced congestion reduction strategies.

Keywords: Value of Travel Time Savings, Willingness to Pay, Contingent Valuation, Priced Lanes, Project Prioritization, Discrete-Continuous Models

1. INTRODUCTION

The value of travel time savings (VTTS) is one of the most widely used concepts in the transportation sector, serving as a critical component of transportation project evaluation, policy formulation, and transportation investment decisions (Mackie et al., 2001; Lehtonen and Kulmala, 2002; Small, 2012; Kono et al., 2018; Small et al., 2024). VTTS represents the marginal rate of substitution between time and money in travel decisions, reflecting how individuals prioritize time savings relative to monetary costs. It is regularly used to translate the travel time savings accrued by travelers from transportation and infrastructure investments (such as building a new road or a new rail line) into equivalent user benefits from an economic (monetary) standpoint (Laird and Venables, 2017; Acampa et al., 2019; Salmani Bishak et al., 2024). Further, VTTS helps in comparing the value proposition of different infrastructure projects, helping prioritize investments given a fixed amount of available funding and human resources, and is critical in the operation of transportation modes (see Oh et al., 2015).

Another important use of VTTS is in the area of pricing for the use of transportation facilities, given that VTTS fundamentally provides a sense of how much users are willing to pay to reduce travel time. Such applications may be in the context of informing how much to charge for a new express bus service that cuts travel time by half, or how much to charge at a certain time of day on ridehailing modes based on demand surges, or how much to charge on roadways (in the form of roadway congestion pricing) for reduced delays based on the level of existing traffic congestion levels. Accurate VTTS estimation in this regard enables not only the prediction of the usage of managed roadway facilities (for revenue forecasting), but also offers behavioral insights to forecast the spatial and temporal effects of pricing on overall travel demand patterns in a region (Kaddoura and Nagel, 2016; Brent and Gross, 2018; Marazi et al., 2024).

In quantifying VTTS, a critical consideration is the recognition that VTTS is not a single number; rather, it varies significantly across individuals and across travel contexts (see Shires and de Jong, 2009; Wardman et al., 2023; Dannemiller et al., 2023). Explicitly accounting for such systematic heterogeneity in VTTS across different demographic groups and travel contexts helps inform decisions related to (a) where roadway congestion pricing may be most effective (for an optimal balance of revenue collections and travel time savings), (b) which groups of travelers will be most likely to utilize priced lanes, and (c) how the benefits of such pricing policies will be distributed across transportation users (Jing et al., 2024; Yu et al., 2025). In contrast, ignoring such VTTS variations can (a) distort demand forecasts for priced lanes (causing them to be underutilized or leading to excess demand that limits actual travel time savings for users), (b) lead to poor estimates of revenue potential, and (c) cause unforeseen activity-behavior changes due to differential influences on trips undertaken for different purposes (Hensher and Goodwin, 2004; Kono et al., 2018). Further, in terms of appraisal (which generally relies on equity-adjusted VTTS values to evaluate the distribution of benefits across population groups), ignoring heterogeneity can lead to misrepresentation of who benefits and who faces additional costs due to a transportation project or policy. Importantly, these considerations of VTTS (and its heterogeneity) are not only relevant for congestion-responsive pricing, but also apply to the design and operation of tollways as it affects the feasibility of toll projects through revenue potential. While there are some differences between congestion pricing and tolling, the fundamental cost-based difference is that congestion pricing can fluctuate substantially across different times of the day at the same location, while tolls tend to be rather flat with little to no variation. In this regard, it is also important to consider individuals for whom VTTS is zero, effectively those who never will use a toll road. Since some individuals may never be willing to pay for travel time savings (as discussed in more detail

later), it is important to accommodate these individuals when determining pricing policies alongside the VTTS among those who may be willing to pay (because the toll price determines the demand capture on these roadways through toll elasticities).

Roadway congestion pricing has been implemented for more than two decades in cities such as Singapore and London that pioneered and implemented the concept. However, it has only received attention more recently in Indian metropolitan regions, a result of the convergence of (a) extreme traffic congestion (and resulting air quality and public health problems), (b) a burgeoning middle-class that has the financial wherewithal to pay for time-savings, and (c) effective, economical, time-tested (in other cities in the world), and labor-light automated toll-collection technology (Sahu et al., 2024; Jha, 2025). For instance, in 2018, a pilot congestion pricing experiment was undertaken in Bengaluru (see Kreindler et al., 2018), a similar pilot is being designed at 13 border points of entry into the Delhi-NCR metro area during peak morning and evening hours (see Nair, 2025), and the National Highway Authority of India (NHAI) has implemented a pricing scheme on the Jaipur-Bandikui linkway (see Basu, 2025). And, in Mumbai, there is an initiative by State authorities to combine transit service improvements with congestion pricing in and around central business districts and downtown areas such as Bandra-Kurla complex, Nariman Point, Worli and Lower Parel (Sen, 2025).

Motivated by the discussion above, the objectives of this paper are to quantify how VTTS varies across individuals and travel contexts as well as to identify those individuals who are unwilling to pay any amount for travel time savings. We do so within the context of the growing transportation infrastructure build-up and roadway pricing expansion in India using a sample of Mumbai residents. Specifically, using data from the Mumbai Household Travel Survey, we develop a joint model that includes a binary outcome indicating whether each individual is willing to pay (WTP) at all to reduce their travel time and a continuous outcome representing the value of travel time savings for those who are willing to pay to reduce their travel time, examining how these choices are influenced by individual, household, and trip-level characteristics. We then use these estimates to examine variations in the VTTS across individuals, trip purposes, travel modes, and time-of-day to provide insights that can inform infrastructure investments and policies aimed at travel time reduction as well as the development of priced lanes in the Mumbai region.

The remainder of the paper is organized as follows. Section 2 provides an overview of the existing literature on VTTS, focusing on assessments of VTTS heterogeneity as well as the approaches used to measure VTTS. Section 3 presents the methods employed in the current study, including the survey administration and modeling approach used. Section 4 includes the model estimation results as well as measures of model fit. Section 5 presents the methods used to translate the model results of the discrete and continuous VTTS components into tangible estimates for policy development and discusses the policy implications of the observed VTTS heterogeneity. Finally, Section 6 concludes the paper with an overview of the important findings and potential future research directions.

2. LITERATURE OVERVIEW

2.1 Travel Context and Heterogeneity in VTTS

As described above, the value of travel time savings (VTTS) quantifies the trade-off individuals are willing to make between time and money, reflecting the economic principle that time has an opportunity cost (Tveter, 2023). While many approaches have proxied VTTS by the wage rate, in recognition of the generally increased economic resources of higher-income individuals relative to temporal resources (Becker, 1965; De Serpa, 1971), research across diverse contexts has

consistently demonstrated that VTTS is not uniform across population groups or travel contexts even after accounting for wage rate (for a few foundational examples, see MVA Consultancy et al., 1987; Hague Consulting Group, 1990). This multi-dimensional heterogeneity has important implications in practice, as individuals with different VTTS will respond differently to interventions such as priced lanes, and accrue different benefits from transportation investments. In fact, Kono et al. (2018) demonstrate that considering a single across-the-board VTTS (ignoring that VTTS is a function of even one aspect of the travel context of a trip – in their case, trip travel time) can lead to significant biases in travel demand forecasting. Thus, a wide range of existing studies have examined how VTTS is dependent on individual sociodemographic characteristics and different aspects of the travel context.

In terms of individual sociodemographic characteristics, income has been shown repeatedly to significantly influence VTTS (see, for example, Jara-Diaz and Guevara, 2003; Börjesson et al., 2012; Athira et al., 2016; Binsuwadan et al., 2023). However, a much broader range of factors have also been found to affect VTTS, including characteristics such as age, gender, and level of educational attainment (Kim and Yook, 2018; Bouscasse and de Lapparent, 2019; Fournier and Christofa, 2021). In an Indian setting, Karmarkar et al. (2023) evaluated VTTS for high-speed rail (HSR) travel, noting substantial heterogeneity based on income levels and age, as well as on the presence of accompanying passengers.

In terms of an emphasis on travel context, mode and trip purpose are commonly considered travel context variables considered to influence VTTS, and variations based on these variables are more readily applied in practice than those based on sociodemographic characteristics or other types of travel context variables (Batley et al., 2019; Wardman et al., 2023; Hartwig et al., 2024). Beyond these, Bouscasse and de Lapparent (2019) observed that perceived ease of travel and positive emotional experiences during travel can reduce VTTS (especially on public transport). Similarly, Meunier and Quinet (2015) and Mishra et al. (2018) noted that comfort and travel time reliability perceptions affect VTTS. Further, beyond the focus on VTTS in human-driven vehicles, Kolarova et al. (2018) explored VTTS variations between human-driven and automated driving scenarios, observing that individuals expressed a lower VTTS in the automated driving scenario (presumably because of reclaiming time that would have otherwise been spent behind the wheel). Finally, Shires and de Jong (2009) and Wardman et al., (2023) undertook extensive meta-analyses of VTTS estimates across different regions, identifying substantial VTTS variations across geographies.

In addition to examining sociodemographic and travel context based VTTS heterogeneity, there has been some debate in the literature about whether VTTS needs to be necessarily strictly positive. In this regard, there is evidence that in many circumstances it is possible to have a VTTS of zero. For instance, an individual may enjoy traveling and may prefer not to reduce trip time. Or an individual may feel a sense of freedom and empowerment from the very act of driving, perceiving “pay-for-travel time savings” as diminishing that empowerment (Fujii et al., 2004; Hsieh, 2022). Or an individual may have a substantial time gap (relative to the travel time) between two scheduled activities, so that travel time savings provide no tangible benefit (Cirillo and Axhausen, 2006; Jara-Diaz, 2024). It is also possible that some individuals may be unwilling to pay for any amount of travel time savings, not because they would not receive value from the time savings, but because of reasons such as institutional distrust or fairness concerns (for instance, believing that road users should not need to pay to use public roads or that funds received from such programs will be misallocated; see Manville and King, 2013; Eliasson, 2016; Selmoune et al., 2020). Thus, some individuals may simply be entirely insensitive to travel time savings (that

is, have a VTTS of zero) and may be systematically different from those who are willing to pay at least some positive amount for travel time savings (we discuss this issue in more detail in the following section).

2.2 Methods for Estimating the Value of Travel Time Savings

2.2.1 Imputation Approach

The most common approach to estimate VTTS has been based on an imputation from the choice made among alternatives with different costs and times. Such an approach follows directly from time-allocation theory, in which travel time and monetary expenditures jointly constrain an individual's utility, yielding an equilibrium marginal rate of substitution (De Serpa, 1971). The choice made, when analyzed from the standpoint of a compensatory decision process (such as utility maximization), effectively reveals this time-cost tradeoff (see, for example, González, 1997; Antoniou et al., 2007; Small, 2012; Li et al., 2020; Coppola et al., 2024). For instance, the approach would involve collecting travel mode choice data and estimating a utility-maximizing discrete choice model for the preferred mode, with coefficients reflecting the relative value of monetary cost and time cost in mode choice utilities. The ratio of the time to cost coefficients would then be imputed as an estimate of VTTS.

The data used in imputation-based studies may originate from revealed preference (RP) surveys, stated preference (SP) elicitations, or a combination of both. Additionally, the travel dimension being analyzed may be mode choice, or time-of-day choice, or other travel choices (the only requirement is that the attributes of the alternatives in the choice process involve both travel time and travel cost). RP data-based studies derive VTTS from actual behavioral choices. For instance, recently, Hartwig et al. (2024) used RP data to estimate VTTS based on travel mode choices, finding a lower VTTS for rail users who can utilize travel time productively. In another recent study, Tveter (2023) used real-world travel pricing variations and aggregate travel count data (obtained from automatic traffic count data) in Norway to estimate VTTS based on changing demand due to day-to-day cost shocks. However, such RP studies have less flexibility to explore specific emerging travel scenarios, and are more susceptible to multicollinearity between time and cost attributes (Meunier and Quinet, 2015; Tveter, 2023). SP data-based studies, such as those by Bradley and Gunn (1990), Beck et al. (2017), and Ojeda-Cabral et al. (2018), enable researchers to design controlled experiments that isolate specific attributes (such as reliability, congestion, or long-term decision contexts) and assess traveler responses to hypothetical scenarios. For instance, Wardman et al. (2020) demonstrated that when travel time is perceived as productive, the value of travel time savings decreases, illustrating the sensitivity of VTTS to how time use is framed. However, SP estimates are subject to hypothetical bias and may not fully capture real-world constraints or habits. Specifically, as shown by Fayyaz et al. (2021), the way the SP questions are posed and worded can have a substantial effect on imputed VTTS. Finally, a variety of authors have combined RP and SP data, leveraging the benefits of matching real-world behavioral choices through the RP data with systematic variation in attributes as presented in the SP portion to break high multicollinearity problems in time and cost (Bhat and Castelar, 2002; Bhat and Sardesai, 2006; Schmid et al., 2022; Tabasi et al., 2023).

While providing a reasonable approach to estimate VTTS, two challenges arise when using the imputation-based approach, regardless of the specific elicitation method (RP, SP, or a combination) employed. First, the approach allows the consideration of VTTS heterogeneity in only a rather limited fashion, through the estimation of separate models for different market segments or by including interaction terms with individual characteristics (such as including an

interaction between cost and income to accommodate a higher VTTS for higher-income individuals). However, including a large number of segments or interaction terms leads to a rapid proliferation in the number of parameters to be estimated as well as introduces multicollinearity across interaction terms (see Fournier and Christofa, 2021; Tabasi et al., 2023). Of course, approaches that accommodate random taste variation (see, for example, Bhat, 1998; Hess et al., 2005; Fosgerau, 2006; Rubite and Muromachi, 2008; Bhat and Lavieri, 2018; Parmar et al., 2023; Bhat et al., 2025; Hayes and Venter, 2025) do allow for unobserved heterogeneity in VTTS through random coefficients and may be combined with interactions to let distributional moments vary with demographics or travel context. However, such random parameter approaches still face issues with the proliferation of parameters and potential multicollinearity when attempting to capture a large amount of systematic heterogeneity in VTTS. Also, the characterization of random heterogeneity is itself highly sensitive to the assumed distributional form (Fosgerau, 2006; Tabasi et al., 2024; Bhat et al., 2025). Thus, it is critical to capture as much heterogeneity as possible through systematic means, leaving as small of an amount as possible to idiosyncratic variation for capture through random taste variations. Further, while random coefficient approaches do accommodate unobserved heterogeneity in VTTS, this only captures the *presence* of preference differences across individuals, not the actual drivers of that variation, so these approaches do not provide the policy-relevant insights in the ways that VTTS varies across demographics and travel context. As such, random taste variations should not be viewed as a substitute for efforts to, first and foremost, capture as much heterogeneity as possible through systematic means (see Bhat, 2000). Second, the imputation approach implicitly assumes that there is a single continuous distribution for VTTS (this is the case even in random coefficient approaches), with no systematic distinction in individual and travel context characteristics between those who are unwilling to pay any amount for travel time savings at all and those who are willing to pay some positive amount. As suggested in the previous section, these travelers must be distinguished if individuals who are unwilling to pay for travel time savings differ systematically from those who are willing to pay some positive amount at least during some travel contexts and low pricing circumstances. Relatedly, the implicit continuous distribution assumption embedded in the imputation approach ignores the clustering of VTTS at the zero point caused by those unwilling to pay any amount for travel. That is, the VTTS distribution is a mixture of discrete and continuous parts, not just a single continuous distribution. Ignoring this aspect will, in general, lead to inconsistent effects of sociodemographic variables and travel contexts on VTTS, as well as inconsistent VTTS imputations themselves.

2.2.2 Direct Measurement Approach

In contrast to the imputation-based approach described above, some studies have taken a more direct approach to measuring VTTS, in which individuals are asked, within a specific choice context, direct questions about how much they value their time, or whether they are willing to pay a specific price for different amounts of travel time savings. Also referred to as the “contingent evaluation (CV) approach” in the economics and marketing literature (see, for example, Boyle et al., 1985; Hoyos and Mariel, 2010; Mitchell and Carson, 2013), this measurement approach asks respondents directly to provide information about how much they would be willing to pay to become beneficiaries of a particular program (in the congestion pricing context, this would be the amount they are willing to pay to use a priced lane that would provide a specific delay reduction). In the transportation literature, such methods are also commonly referred to as Transfer Price (TP) or Transfer Time (TT) methods (Dalvi and Lee, 1971; Bonsall, 1985; Daly and Gunn, 2002),

focusing on the change in price or travel time that would cause the respondent to switch (or “transfer”) from one alternative to another (in the congestion pricing context, this would be the amount of travel time savings to have them switch from a free route to a priced route). Such approaches have not been routinely used in the transportation context because, when tied to SP mode choice experiments, there are concerns that unobserved mode preferences (beyond variations in the actual cost and time attributes considered) may bias the valuations of TP/TT (see Bonsall, 1985). In contrast, while TP/TT applications generally focus on switching behaviors, CV methods have retained their attractiveness in contexts where attribute effects remain relatively isolated (primarily for policy changes or unlabeled choice switching). That is, in scenarios that isolate a single policy-relevant change, CV methods can be more effective than SP choice experiments because attribute effects can be evaluated independently, avoiding concerns of confounding influences and preferences tied to the choice alternatives or to other attributes considered in the choice experiment (Armbrecht, 2014; Boyle, 2017; Steigenberger et al., 2022). Thus, in the current pricing context, we apply CV to the case of choosing a priced lane, isolating the relative values of monetary and time costs separate from mode switching effects.¹

Multiple methods may be adopted under this CV approach, including asking respondents to provide the specific amount they are willing to pay (open-ended method), requesting a “yes” or “no” vote to a single specified price for a policy (referendum method), or asking respondents iteratively whether they would be willing to pay each specific offered price in a series of increasingly-priced bids (iterative bidding method). This final iterative bidding method can be particularly effective relative to other CV methods because (in contrast to an open-ended method) it is relatively straightforward for respondents to respond to the binary outcome at each offered price level rather than requiring respondents to generate their own precise value (Bishop and Heberlein, 1990; Sajise et al., 2021), and because (in contrast to the referendum method) it can obtain a good point estimate of the actual VTTS for an individual rather than a censored range of VTTS. One limitation of the iterative bidding method is the potential for starting-point bias. That is, unlike the open-ended method, respondents may anchor their valuations to the initial bid presented. However, this concern is likely to be limited in our application because it entails a relatively low-cost valuation setting, as well as because our framing draws on respondents’ real-world experiences that provides them with a well-formed sense of their own valuation prior to encountering their first bid (Herriges and Shogren, 1996; Aprahamian et al., 2008; Veronesi et al., 2011). Indeed, Green et al. (1998) and Mussweiler and Strack (2000) argue that starting point bias is most pronounced when respondents face substantial uncertainty about their preferences of the decision context. When the valuation task is grounded in familiar, concrete experiences, such uncertainty – and therefore the scope for anchoring – is reduced. Similarly, Schmidt and Bijmolt (2020) find that anchoring effects are considerably stronger for high-value, infrequently purchased luxury goods, but comparatively modest for lower-value, routine expenditures such as paying for travel time savings, while Berg and Moss (2022) demonstrate that anchoring effects are reduced when the initial bid is set at a relatively low level as in our design rather than at a high starting

¹ Our CV approach with a fixed time change and varying cost bids is a close counterpart to a two-alternative SP design in which the non-monetary attribute is held constant. The key distinction we see is that CV typically fixes the improvement and directly elicits the willingness to pay for that specific change, emphasizing welfare measurement. In contrast, a simple SP experiment trading off time and money allows both attributes to vary across repeated choice tasks and estimates VTTS indirectly from observed trade-offs, emphasizing structural preference recovery. For this reason, CV and simplified binary SP are closely related instruments. In the current research, we employ a CV approach because our goal is to estimate a direct welfare measure for a defined improvement, rather than to estimate a broader behavioral model.

value. Further, the iterative bidding method allows for the direct calculation of VTTS for each individual, so that VTTS can be modeled as an outcome itself, allowing for a straightforward analysis of exogenous variable effects on VTTS (including connecting VTTS directly to variables relating to the travel time and time savings). Of course, the iterative bidding method results in a small bounded range of VTTS for each individual rather than an exact point estimate. However, in practice, many “continuous” open-ended survey responses also reflect rounding or focal-point behavior, so the apparent precision of a single stated value may overstate its true information content. The iterative bidding approach provides a useful alternative by decomposing the valuation task into a series of simpler comparisons, thereby reducing cognitive burden and limiting the scope for strategic overstatement (Andersson and Svensson, 2008; Johnston et al., 2017), even if the resulting estimate is expressed as a narrow interval rather than a single point. Besides, the method obtains information on those individuals who are unwilling to pay any amount at all to reduce travel time savings, thus enabling the distinction of such individuals from those who are willing to pay at least occasionally under the right circumstances. From an econometric estimation standpoint, the method also allows the explicit recognition of the discrete-continuous nature of the VTTS distribution among users.

2.3 Contributions

Building on the large body of research on VTTS, this study contributes to the literature in several behavioral and methodological ways. First, we examine VTTS as elicited in a CV approach using the iterative bidding design method. Further, these questions are asked in the context of the trip taken most frequently/regularly by each respondent, allowing respondents to draw on their actual travel experiences, perceptions, and real-world context when evaluating potential travel time savings. This combination of the bidding approach (that helps respondents come to a reasonable numeric value for their value of travel time savings) with the positioning of the question in the context of a familiar trip (after eliciting details about this trip) helps alleviate hypothetical bias that may more strongly affect traditional stated elicitation methods. Second, we identify respondents who are unwilling to pay at all for travel time savings (are unwilling to pay at the lowest price level offered). By considering this binary willingness to pay (WTP) dimension separately from the continuous VTTS dimension, we provide a strong behavioral and econometric foundation for the analysis. Third, we consider systematic heterogeneity in VTTS across a wide range of individual sociodemographic and trip characteristics, unraveling significant variations across the population and across travel contexts that would not be as easily identified using an imputation-based approach. From a policy standpoint, characterizing this heterogeneity systematically has important implications for prioritizing transportation investments, understanding the distribution of impacts of delays and travel improvements, and designing effective transportation pricing strategies. Also, while many recent studies have captured heterogeneity in VTTS through random taste variation (see, for example, Bhat, 1998; Hess et al., 2005; Fosgerau, 2006; Rubite and Muromachi, 2008; Bhat and Lavieri, 2018; Parmar et al., 2023; Bhat et al., 2025; Hayes and Venter, 2025), such random effects should not be considered as a substitute for capturing systematic heterogeneity, especially when the objective is to inform policy discussions and identify effective pricing strategies. Fourth, we jointly model the binary WTP dimension alongside the continuous outcome for the value of travel time savings among those with a positive willingness to pay. As individuals with a VTTS of zero are accounted for in the WTP binary outcome, the continuous VTTS value is distinct from the total VTTS, instead representing the conditional value of travel time savings that is only available for those who are willing to pay (labeled “*cVTTS*” to denote the continuous

component of the total VTTS). Such a separation creates a two-outcome discrete-continuous structure that naturally corresponds to what is often described in the economics and labor supply literature as the “extensive” and “intensive” margins of behavior (see Saez, 2002; Blundell et al., 2013; Fernandes et al., 2023): the binary WTP decision captures the extensive margin (whether an individual is willing to pay for time savings), while the continuous $cVTTS$ outcome reflects the intensive margin (how much the individual is willing to pay per unit of time saved, conditional on being willing to pay at all). The separate (but joint) modeling of these two outcomes also accommodates the presence of unobserved correlation effects that occur between the WTP and $cVTTS$ dimensions, accounting for “self-selection” due to the fact that $cVTTS$ is likely to be higher among those with a positive WTP relative to a random individual drawn from the larger population of all individuals. For instance, an individual with a more impatient or impulsive attitude may be more likely to be willing to pay in general to avoid travel delays due to greater feelings of urgency. At the same time, these more impatient individuals, even after crossing any psychological barrier to paying at all, may be willing to pay a higher amount for each minute of travel time saved relative to another random observationally-identical individual in the larger population. The net effect would be a positive correlation between WTP and $cVTTS$. Finally, we use the model results to quantify the total VTTS (accommodating those who are unwilling to pay at all as well as those with a positive WTP) in different population subgroup and trip market segments.

3. DATA AND METHODOLOGY

3.1 Data Description

We use data from a household travel survey conducted in 2024 in the metropolitan region of Mumbai, including Navi Mumbai (or New Mumbai), in India. The survey questionnaire closely follows the US NHTS (National Household Travel Survey) format and contains household, vehicle, person, and trip (24-hour travel diary) modules. In addition, the survey elicits details regarding congestion pricing acceptability and willingness to pay to avoid travel time delay. The complete Mumbai travel survey dataset obtained information from 3,107 individuals across 1,531 households. The survey administration approach employed a stratified random sampling method, using vehicle ownership and residential neighborhood population density as the two key strata-defining variables. The survey covers 20 of the 24 municipal/administrative wards in the Mumbai (Brihanmumbai Municipal Corporation) area and the six most prominent residential and employment zones within Navi (or New) Mumbai (including Nerul, Belapur, Koparkhairane, Airoli, Vashi, and Ghansoli). The survey also encompasses a wide range of ward/zone densities, ranging from about 4,000 persons per square kilometer (in Ghansoli, Navi Mumbai) to more than 65,000 persons per square kilometer (in Dharavi, Dadar, and Bhuleshwar). Samples were drawn in proportion to ward/zone populations to cover the entire spatial extent of the metropolitan region and capture the spatial heterogeneity of the Mumbai metropolitan area, including Navi Mumbai. However, since specified quotas (based on vehicle ownership) were assigned to each stratum (with an upper cap of 1500 households, given the resource constraints), the survey results are not representative of the resident population of Mumbai/Navi Mumbai. For instance, about half of the households surveyed are car-owners, and 70% have at least one vehicle (a car or motorized two-wheeler) in their household. For reference, the per-capita private vehicle ownership in Mumbai was about 13% in 2015 (*Comprehensive Mobility Plan (CMP) for Greater Mumbai*, 2016). For this reason, aggregate descriptive statistics derived from this analysis should not be generalized to the broader Mumbai population. However, despite differences between the characteristics of survey respondents and the broader Mumbai population, weighting is not required for the

individual-level disaggregate analysis undertaken in the current study. The objective here is to estimate individual-level causal relationships between observed characteristics and VTTS. Under stratified but exogenous sampling (that is, individuals are not selected into the sample based on their VTTS values), consistent estimation does not require weighting to make the sample representative of the population (see Solon et al., 2015 and Robbennolt et al., 2026 for detailed discussions of why weighting is not necessary to derive individual-level relationships in such exogenous sampling situations). The more important issue is the presence of sufficient variation in the exogenous variables of interest (as discussed further in Section 3.1.2).

3.1.1 Outcome Variables

The two outcome variables considered in the current model are (a) a binary discrete variable indicating whether each individual is willing to pay (at all) to reduce their travel time (labeled “WTP”), and (b) a continuous variable representing the value of travel time savings among those who are willing to pay (labeled “ $cVTTS$ ”). To determine these outcomes, participants were asked if they used a personal car “frequently/regularly” for traveling in Mumbai. Those that did use the car mode “frequently/regularly” were asked about the trip they took most frequently using their personal car. Individuals who reported that they did not travel “frequently/regularly” with a personal car were asked about the trip taken most “frequently/regularly” with app-based ridehailing, taxi, or autorickshaw, and asked to specify which of these three modes was the primary mode used for these selected trips. Of the 3,107 survey respondents, 1,031 used a private vehicle “frequently/regularly” and responded based on the characteristics of their most frequent car trip, while an additional 1,066 used ridehailing, taxi, or autorickshaw “frequently/regularly” and reported the characteristics of the trip taken most frequently using one of these modes. The remaining 1,010 individuals reported not using any of these modes “frequently/regularly.” The vast majority of these individuals reported using walking and public transit as their primary means of transportation. In any case, these 1,010 individuals were excluded from the iterative bidding exercise in the survey, and so do not feature in the remainder of the analysis. The vast majority of these individuals reported using walking and public transit as their primary means of transportation, and were excluded from this exercise in the survey. Walking entails no monetary travel cost and is not directly affected by congestion charging. Public transit users are typically exempt from congestion charging schemes, which function similarly to Pigouvian taxes (Pigou, 1920) designed to internalize the social and environmental externalities associated with private vehicle use (Anas and Lindsey, 2011; Moulin and Urbano, 2025). In many cases globally, congestion charging revenues are reinvested in public transit and other relatively sustainable modes (D’Agostino et al., 2020; Veitch and Rhodes, 2024). Moreover, when lane or road pricing is used to manage travel demand along highly congested corridors, priced facilities are often made available to certain public transit services without additional charges to encourage transit adoption (Newmark, 2014). Consequently, the policy relevance of estimating VTTS for congestion delay reduction among regular public transit users is more indirect than for private motorized modes. Additionally, in the Indian context, many public transit users tend to have relatively lower incomes and rely on highly subsidized services with dedicated rights-of-way in certain corridors (Shaban and Sattar, 2023; Sarath et al., 2026). For these reasons, the current study focuses on motorized road-based modes directly subject to congestion pricing, while recognizing that future work could explicitly examine transit-user VTTS in alternative policy contexts.

Next, for each respondent, based on their most frequent trip-mode combination, the survey sought information on the “usual travel time,” the “worst case travel time,” and the “travel time

when there is no traffic congestion (imagine traveling at 2 AM).” Next, respondents were asked whether they would be willing to pay to save time on this route. The travel time savings were presented as the difference between the “usual travel time” and the “travel time when there is no traffic congestion,” simulating the addition of a priced lane along the respondent’s route that would operate at free-flow speeds (the median offered travel time savings based on these values was 15 minutes, the mean travel time savings was 20 minutes, the minimum was 2 minutes, and the maximum was 95 minutes; also, when eliciting the travel time savings, the question specifically mentioned the potential of a priced lane being available that users could pay to use to get the reduced travel time). Notably, the framing of the question around the respondent’s travel time estimates does not rely on them making completely accurate objective predictions of these values, but instead creates a respondent specific anchor for what a congestion-free version of their regular trip would look like. Thus, this approach is essentially a pivot design that generates values for delay reductions that are customized to the trips of each individual, improving the realism and credibility of the experiment (Train and Wilson, 2008; Haghani et al., 2021). For this customized potential delay reduction, respondents were asked whether they would be willing to pay 50 rupees² to get the delay reduction (those that were not willing to pay 50 rupees were assigned the value of zero for the binary WTP outcome, while those who were willing to pay 50 rupees were assigned the value of one).³ Then, respondents who were willing to pay 50 rupees were asked iteratively whether they would pay higher amounts in 50 rupee increments until they were no longer willing to pay the requested amount. These requests were made up to a maximum of 1000 rupees or 20 iterative bids (though the value of travel time savings had more variability and could be much higher, as the travel time savings presented to each respondent was generally much less than an hour), and 76% of respondents rejected a bid within the first eight requests. To calculate the *cVTTS*, the highest amount that a respondent was willing to pay (the last value offered to them that they accepted was taken as the highest amount that they were willing to pay) was divided by their potential delay reduction. Thus, the time savings presented corresponds to a reduction in congested time, and the *cVTTS* elicited reflects the stated monetary value attributed to this reduction. One limitation of the iterative bidding CV design, as described above, is that the elicited values may be affected by starting-point anchoring (Boyle et al., 1985; Johnston et al., 2017). In the current

² At the time of data collection, 50 rupees corresponded approximately to the cost of a vada pav (a popular street food in Mumbai) or the cost of a one-day second class local train pass. The median *cVTTS* in the sample of approximately 600 rupees per hour corresponds roughly to the cost of two cups of coffee at a café in Mumbai. Also, expressing this median *cVTTS* as a proportion of the wage rate yields approximately 1.29 (using a wage rate of 463.89 rupees per hour; see Economic Research Institute, 2025), a comparable estimate to those of Wardman et al. (2023) for the value of travel time savings under congested conditions.

³ Notably, it is possible that some individuals who are unwilling to pay at least 50 rupees for travel time savings may still be willing to pay some positive amount, but less than the 50-rupee starting point. However, due to the low initial bid of 50 rupees (particularly for those with relatively long travel time savings), we refer to these individuals who are not willing to pay at least 50 rupees as being “unwilling to pay for travel time savings.” We recognize the limitation in potentially capturing some individuals with very low VTTS in this category and recommend that future studies specifically query such respondents about (1) their willingness to pay at even lower amounts and (2) their specific motivations for being unwilling to pay or reporting an unwillingness to pay (such as strategic non-payment attitudes, skepticism about the effectiveness of pricing schemes, and a general reluctance to engage with hypothetical payments). But, in practical planning and pricing applications, whether these individuals have a true zero valuation or an effectively zero valuation due to resistance to paying or other reasons is less consequential than the fact that they are likely not to use priced facilities. So, while the potential for hypothetical bias does remain, as with any SP exercise, our approach of separating the binary WTP from the continuous *cVTTS* (along with the already mentioned strategies of using a modest starting bid and grounding the choice in real-world scenarios) helps minimize the risks of such biases.

context, however, the relatively modest cost of travel time savings, particularly for short trips, means that a relatively low starting point of 50 rupees, which also matches the increment size, may be used, and a good range of reasonable VTTS values may be covered without an excessive number of bids, helping to reduce the scope for this concern. Also, as mentioned previously in Section 2.3, the use of an actual trip that respondents routinely take puts respondents in a familiar context, allowing them to draw on their own experiences of travel and the delays they actually experience, providing more credibility in the $cVTTS$ value derived from the iterative bidding exercise and also helping to mitigate such anchoring effects.

Of the 2,097 respondents considered, 1745 (83.21%) were willing to pay at least 50 rupees to reduce their travel time, while the remaining 352 (16.79%) were not. There is no clear benchmark from other studies in the Indian context to compare these statistics with. The one study that comes somewhat close as a benchmark is by Marazi et al. (2022), who found that around 60% of respondents in Hyderabad (another fast growing city in India) were unwilling to accept congestion pricing. While substantially higher than the 16.79% who will not pay even 50 rupees for a reduction in travel time savings, it must be pointed out that the Marazi et al. study did not provide a specific price point for travel time savings. Without such pricing information, respondents may have assumed that they would have to incur a higher price for congestion relief than their own VTTS, leading to the high share saying they find congestion pricing unacceptable. Besides, the question posed in the Marazi et al. study was related to whether respondents would accept congestion pricing, not whether they would be willing to pay some amount for congestion pricing. Also, it is worth noting that Mumbai ranks among the most severely congested cities in India and globally (TomTom, 2025), suggesting that Mumbai commuters face acute time costs from congestion and may therefore be more willing to pay for travel time savings. Figure 1 shows the distribution of values of travel time savings disaggregated by trip mode. The first mass on the left of each subfigure shows the number of respondents who were unwilling to pay for travel time savings, while the distribution of values on the right shows the $cVTTS$ among those willing to pay for travel time savings. As may be observed in the figure, the $cVTTS$ distribution is right-skewed, while the distribution of the logarithm of $cVTTS$ is relatively symmetric. Besides, the $cVTTS$ value must be positive, so the logarithm of $cVTTS$ is included as the continuous outcome in the model.

From the first bar chart in Figure 1 on the left, the $cVTTS$ appears to be higher for the non-car modes (taxi, ridehailing, and autorickshaw) compared to those traveling by car, particularly among taxi users (the proportion of respondents with non-car modes rises in the bar charts with an increase in $cVTTS$ value). The average $cVTTS$ across all modes is approximately 1,060 rupees per hour, while the median is around 600 rupees per hour. Although this average value is larger than those of other recent findings in the same geographic context (see Varghese and Jana, 2018 and Karmarkar et al., 2023), it is compatible with estimates of Wardman et al. (2023) for urban private vehicle travel (after accounting for India's GDP per capita) based on a large meta-analysis of 35 low- and middle-income countries. The slightly higher value in our sample compared to some recent estimates in the Mumbai area is also not surprising because (a) this average $cVTTS$ is calculated only for those who are willing to pay for travel time savings, leading to a higher $cVTTS$ compared with the overall VTTS reported in these earlier studies, (b) our focus is on individual-level motorized modes only, while these other studies are focused more on public transit options, and (c) the sampling mechanisms targeted a large share of car owners, which skewed the sample towards higher-income individuals who are likely to have higher values of travel time savings. However, as noted earlier, this skew is a non-issue for estimating individual-level causal relationships to identify the factors affecting VTTS.

3.1.2 Exogenous Variables

The exogenous variables considered include individual and household characteristics and the details of the trip under consideration. Descriptive statistics for these variables are presented in Table 1. As may be observed, there is a good distribution across the individual and household characteristics, which is the key to estimating cause-effect relationships between exogenous variables and endogenous outcomes.⁴ As far as trip characteristics, respondents were asked to provide the mode, trip purpose, cost (for those using rickshaws, ridehailing, or taxis), trip distance, frequency with which they make the trip (all trips under consideration occur at least weekly), time of day they usually make the trip, and whether they share a ride with anyone else (for car travel, sharing a ride was defined as traveling with one or more additional individuals; for the other modes, sharing a ride was defined as traveling with one or more additional passengers).⁵ As mentioned earlier, they are also asked to provide an expected travel time, free flow travel time, and congested travel time. From these, in addition to constructing their $cVTTS$ value based on the amount they are willing to pay (the continuous endogenous outcome), we calculate the proportion of their expected travel time that they would save by choosing the delay reduction, and the proportion of the maximum delay (the difference between the congested travel time and free flow travel time) that they would expect to save. This latter quantity gives an estimate of their trip travel time reliability, with higher values indicating that the travel time is fairly reliable and lower values indicating a higher degree of uncertainty in travel time (thus, for example, a delay reduction of 10 minutes for a relatively reliable trip – say a low difference between maximum delay and free flow time of 20 minutes – would yield a proportion estimate of maximum delay saved of 0.5, while the same delay reduction of 10 minutes for a more unreliable trip – say a high difference between maximum delay and free flow time of 40 minutes – would yield a proportion estimate of maximum delay saved of 0.25).

3.2 Model Formulation and Estimation

The model comprises a single binary outcome (for the WTP) and a single continuous outcome (for the logarithm of the $cVTTS$), is the latter being relevant only among those who are willing to pay. The model is estimated as a single joint system with a bivariate normal error structure to accommodate unobserved correlations across the WTP and $cVTTS$ components. For the WTP outcome, consider the latent propensity z_q^* that is mapped to the binary outcome z_q for whether an individual q is willing to pay at all ($z_q = 1$) or not willing to pay at all ($z_q = 0$) as follows:

⁴ In Table 1, residential population density, categorized as low, medium, and high, was constructed as follows. Respondents were asked to provide their home address, which was used to identify their Ward of residence. Then, the population density of their residential neighborhood was determined at the Ward level and classified into the three levels of (a) less than 21,000 persons per square kilometer (low population density), (b) between 21,000 and 32,999 persons per square kilometer (medium population density), and (c) 33,000 persons per square kilometer (high population density). This classification was selected to segment survey respondents (at the household level, and for the entire survey sample, rather than the subset of 2,097 individuals considered in the current analysis) into three approximately equal categories based on the population density of their Ward of residence.

⁵ Interestingly, in terms of the time-of-day distribution, the vast majority (75.87%) of trips reported in the survey as being taken the most “frequently/regularly” were undertaken in the morning. Thus, in subsequent sections, we distinguish between trips taken during the morning peak period (before 9:30 am) and other times, but do not consider a separate period for the evening peak.

$$z_q^* = \boldsymbol{\gamma}'\mathbf{w}_q + u_q; z_q = 0 \text{ if } z_q^* \leq 0; z_q = 1 \text{ if } z_q^* > 0, \quad (1)$$

where \mathbf{w}_q is a vector of exogenous variables (including a constant) and $\boldsymbol{\gamma}$ is a corresponding vector of parameters to be estimated. u_q represents a standard normal error term that is assumed (for identification reasons) to be independent and identically distributed across individuals in the sample.

Moving to the continuous outcome, we can write the continuous outcome y_q representing the logarithm of the *cVTTS* as a function of covariates as:

$$y_q = \boldsymbol{\beta}'\mathbf{x}_q + \varepsilon_q, y_q \text{ observed only if } z_q = 1, \quad (2)$$

where \mathbf{x}_q is also a vector of exogenous variables (including a constant) and $\boldsymbol{\beta}$ is a corresponding vector of coefficients to be estimated. As noted previously, the logarithmic transformation is appropriate in this case because (1) the *cVTTS* must be strictly positive (after those who are unwilling to pay at all for travel time savings are accommodated through the binary WTP component), (2) the distribution of *cVTTS* is highly right-skewed while the distribution of the logarithm of *cVTTS* is much closer to symmetric (as shown in Figure 1). For identification considerations, we also maintain the usual exclusion restriction that there is at least one variable (“instrument”) that is contained in the vector \mathbf{w}_q , but does not appear in the vector \mathbf{x}_q . ε_q is an error term that is a realization from a normal distribution with mean zero and variance σ^2 . Let the correlation between u_q and ε_q be ρ . Let $\boldsymbol{\tau}$ be the column vector of parameters to be estimated: $\boldsymbol{\tau} = [\boldsymbol{\gamma}', \boldsymbol{\beta}', \sigma, \rho]'$. Using the properties of the bivariate normal distribution, the conditional distribution of z_q^* , given the observed value g of the continuous outcome for the individual, is normally distributed with mean $B_q = \boldsymbol{\gamma}'\mathbf{w}_q + \rho\sigma^{-1}(g - \boldsymbol{\beta}'\mathbf{x}_q)$ and variance $\theta^2 = (1 - \rho^2)$.

For estimation, define C as the set containing the individuals for whom $z_q = 0$, and D as the set containing the individuals for whom $z_q = 1$. Then, the joint likelihood function may be written as:

$$L(\boldsymbol{\tau}) = \prod_{q \in C} [1 - \Phi(\boldsymbol{\gamma}'\mathbf{w}_q)] \times \prod_{q \in D} \left[\frac{1}{\sigma} \phi\left(\frac{g - \boldsymbol{\beta}'\mathbf{x}_q}{\sigma}\right) \Phi\left(\frac{-B_q}{\theta}\right) \right] \quad (3)$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ represent the probability density function and cumulative distribution function, respectively, of the univariate standard normal distribution.

4. RESULTS

The final model specification, shown in Table 2, was developed based on an iterative process of including exogenous variables in various functional forms (see Table 1 for a complete list of variables tested in the specification) and evaluating improvements in statistical fit using both coefficient-level significance (t-statistics) and model fit metrics (including likelihood ratio tests). A variety of interaction effects between sociodemographic characteristics and travel contexts were also explored using a similar iterative approach. Interaction terms were first tested as two-way combinations between each pair of exogenous variables, followed by testing higher-degree

interaction effects between trip-characteristic variables that had strong two-way effects. A t-statistic threshold of 1.65 corresponding to a 0.1 level of significance or 90% confidence level was used to retain variables during this specification process. Identification in our model system comes from an exclusion restriction (a variable appearing in the WTP equation, but not the $\text{LN}(cVTTS)$ equation), and cross-equation parameter restrictions and distributional assumptions.

The main estimation results are discussed next in Section 4.1, followed by a discussion of model fit in Section 4.2. The discussion in this section focuses on the impacts of the exogenous variables on the underlying utility for the WTP outcome and on the logarithm of $cVTTS$ ($\text{LN}(cVTTS)$). These coefficients are important to estimate the WTP and $cVTTS$ for any combination of demographics and trip contexts. A discussion of the magnitude of effects of variables, as aggregated across individuals in the sample, is presented in Section 5. In the case of discrete exogenous variables, the base category is provided in parenthesis. A ‘—’ entry for a coefficient in a specific column indicates that the corresponding row variable does not significantly impact the column endogenous outcome. If the coefficients (and corresponding t-statistics) on two variables are exactly the same (such as the interaction effects of age 35-44 and age 45 and over with work or education trips on $\text{LN}(cVTTS)$), it implies equal effects of the two variables.

4.1 Main Estimation Results

4.1.1 Effects of Individual and Household Characteristics

The results in Table 2 show that women, relative to men, have a higher WTP overall and a higher $cVTTS$ for work or education trips, while also exhibiting a lower $cVTTS$ for maintenance and leisure trips. A greater willingness to pay for travel time savings overall among women, and a higher $cVTTS$ for work/education trips for women, may reflect the time poverty effects among women who have to balance household responsibilities with work/education pursuits (George and Shaji, 2024). The lower $cVTTS$ among women for maintenance pursuits may be a convergence of multiple reasons, including (a) the gendered societal norms and expectations of women as being responsible for maintenance activities, (b) the non-income generating nature of maintenance pursuits, and (c) the typically lower economic bargaining power of women in households that may make it difficult to justify expenditures to lower travel time for maintenance activities (Borah Hazarika and Das, 2021; Deshpande and Kabeer, 2024). Similarly, in a rather male-dominated socio-cultural environment, women’s engagement in leisure activities, especially those that require travel, may be viewed as frivolous or self-indulgent, rather than as legitimate uses of time (Naganathan et al., 2021). This normative pressure can lead to the lower $cVTTS$ among women for leisure.

Older individuals, relative to their younger peers, exhibit a lower WTP and lower $cVTTS$ for work and education trips. This result is unsurprising given that older individuals typically occupy more secure job positions and adhere to well-established routines, both of which can help buffer the effects of transportation delays caused by congestion. Similarly, those with higher levels of formal educational attainment also appear to be less willing to pay for travel time savings and have a lower $cVTTS$, potentially the result of the more productive use of travel time among highly educated individuals (Varghese and Jana, 2018; Lavieri and Bhat, 2019). In contrast, higher income individuals (those with an annual income of 2.5 million rupees or more) compared with lower income individuals (those with an annual income of less than 2.5 million rupees) are generally more willing to pay to reduce travel time and have a higher value of travel time savings for maintenance and leisure trips, consistent with many existing findings (see, for example, Axhausen et al., 2008; Binsuwadan et al., 2023). However, lower-income individuals exhibit a

higher $cVTTS$ for work and education trips, presumably because of the typically stricter on-time work attendance requirements of the type of jobs held by such individuals (Vogtman and Tucker, 2017).

Adults with children in the household (a child is defined as 17 years of age or less), relative to other households, are less willing to pay to reduce travel time for work/education, presumably a result of work/education travel being undertaken around children's transportation needs and scheduled activities, such that travel savings for some trips may merely translate into additional waiting time rather than free time (Schwanen and Ettema, 2009). However, adults with children in the household have a higher WTP for maintenance/leisure trips, and a higher $cVTTS$ for all trips, perhaps due to an elevated perceived value of travel time savings for children themselves compared with the value of travel time savings for adults (see Utsunomiya, 2025). Additionally, in the category of household composition variables, individuals living alone have a lower WTP relative to households with multiple adults and no children, as well as a lower $cVTTS$ relative to all other types of households (including households with children), reflecting the greater flexibility in scheduling and the reduced need for schedule coordination.

Employed individuals have both a greater WTP and higher $cVTTS$ for work and education trips compared with those who are unemployed, underscoring the consequences of congestion delays for workers and the relatively higher economic ability to pay for travel time savings among employed individuals. Finally, within individual and household characteristics, those living in high population density areas have a lower WTP, but also a slightly higher $cVTTS$, relative to those in low or medium population density areas. The lower willingness to pay among those living in high density areas may reflect a habitualization or normalization of travel time delays, while the higher $cVTTS$ may reflect the higher level of perceived time scarcity among urban dwellers, as has been observed in other studies (see, for example, Cho and Parkhomenko, 2024).

4.1.2 Effects of Trip Characteristics

Table 2 shows that, in general, there is a heightened willingness to pay for trips during the morning peak period (before 9:30 am) compared with trips taken later in the day, across all modes and trip purposes. WTP is also higher for those traveling for work and education purposes compared with maintenance or leisure purposes in the "before 9:30 am" period, and even more so for those traveling by car for work- or education-related purposes in this morning period relative to those traveling by non-car modes (taxi, ridehailing, or autorickshaw). Interest in reducing travel time during the early-morning period is unsurprising given that congestion-related delays are much more common during this time, and delays during this period can have a larger impact on time allocation throughout the remainder of the day and on-time arrival at many other scheduled activities throughout the rest of the day (Wardman and Nicolás Ibáñez, 2012; Kim et al., 2023). The $cVTTS$, however, follows a slightly different pattern. For maintenance and leisure trips, the $cVTTS$ is higher for non-car modes (relative to car users) and is relatively stable across the day. In contrast, travel time savings for work and education trips are valued more among those using cars, and particularly so for those using cars and traveling before 9:30 am, mirroring the results from the willingness to pay. The higher $cVTTS$ among car users relative to non-car users for work and education trips may be reflecting the inability to use travel time productively, given car users have to drive the vehicle (Steck et al., 2018; Varghese and Jana, 2018).

Those taking shared trips are more likely than those taking solo trips to be willing to pay some positive amount to reduce travel time, though also less willing to pay high costs to save time. These differential results for WTP and $cVTTS$ may be a combination of users experiencing

discomfort when sharing trips with strangers because of which they are willing to pay some positive amount to reduce time (see Meshram et al., 2020; Shah et al., 2020), but also greater willingness to accept travel delays given they have chosen to share a ride in the first place. Regarding trip frequency effects, individuals have both a lower WTP and lower $cVTTS$ for trips made frequently (2 or more days per week rather than once a week), likely a normalization effect that makes individuals who experience routine delays less sensitive to such delays than those who experience delays less frequently (Karmarkar et al., 2023).

Those who already experience a monetary cost for a trip (taxi, ridehailing, and autorickshaw users encounter such costs) are less willing to pay for travel time savings and have a lower $cVTTS$, reflecting a preference to avoid additional expenses once a cost investment has already been made. The results also show that those with longer expected travel times and higher proportions of travel time saved, in general, are more willing to pay for travel time savings, but also have a lower $cVTTS$ should they actually pay for travel time reduction.⁶ The latter result is consistent with the notion that the marginal value of travel time savings decreases with distance (see Hensher, 1997; Festjens and Janiszewski, 2015; Wardman et al., 2016). Finally, in the group of trip characteristics, those whose delay savings are a larger portion of the maximum delay they ever experience (that is, those who have more travel reliability) are generally less likely to be willing to pay for travel time savings and have a lower value of travel time savings (compared with those whose travel time is less reliable). This result is intuitive, suggesting that travel time savings are most desired among those with high unreliability in travel time, rather than just among those who face significant delays (see Carrion and Levinson, 2012; Fayyaz et al., 2021).

4.1.3 Constants, Scale, and Correlation Terms

The constant terms shown in Table 2 do not have any substantive interpretations. They are estimated to provide the best fit to the share of individuals willing to pay for travel time savings and the average value of the logarithm of $cVTTS$ in the sample. As discussed above, the scale of the binary outcome is fixed to one, but the scale (standard deviation) of the continuous logarithm of the $cVTTS$ and the correlation between the two outcomes may be estimated. The significant positive correlation between WTP and $cVTTS$ is intuitive and suggests that there are common unobserved variables that impact both outcomes. For instance, individuals with more rigid schedules or more time constraints may be more likely to be willing to pay at all for travel time savings and place a higher value on any specific amount of travel time saved.

4.2 Model Fit

Several goodness of fit metrics are shown at the bottom of Table 2, comparing the proposed joint model to an independent model that ignores the jointness between the outcomes (that is, the independent model assumes that the correlation term is fixed to zero). Although the significant correlation term discussed in the previous section already supports the importance of the joint modeling approach, the two models are compared with several additional disaggregate fit metrics. The proposed model has a larger adjusted likelihood ratio index as well as a smaller value of the Bayesian information criterion, suggesting a better data fit compared to the independent model. Further, a likelihood ratio test between the two models yields a chi-square statistic of 31.04, which

⁶ In addition to these two temporal variables, several other time-related variables and functions of the variables were tested (including allowing for the amount of time saved to impact the $cVTTS$ directly). However, the specification with the best statistical fit is the one presented in Table 2 that accommodates travel time through the proportion of the expected travel time that is saved and the proportion of the maximum delay that is expected to be saved.

is statistically significant for a single degree of freedom at any reasonable confidence level. Thus, the proposed model demonstrates a superior ability to predict the multiple outcomes compared to the independent model.

5. QUANTIFYING THE VALUE OF TRAVEL TIME

5.1 Calculating the Value of Travel Time

The model results presented in the previous section highlight the importance of considering heterogeneity in the value of travel time savings across both individual demographics and trip characteristics. However, the results by themselves do not provide a complete picture of VTTS values and the variations in these values, because of the discrete-continuous nature of the modeling system. Thus, there is a need to develop an approach that translates the model results of the discrete and continuous components into tangible insights for policy development, expressly recognizing the joint nature of the two components. To do so, we compute three metrics for each of several travel scenarios. First, we estimate the proportion of individuals in the population willing to pay (at all) for travel time reductions, a metric that provides insights into market penetration, indicating what portion of users would even consider using faster priced options such as toll lanes or would support congestion pricing policies. Note that this is not a willingness to pay based on a set price for travel time savings, but a willingness to pay at all for travel time savings (corresponding to the binary WTP in our model system). Second, we calculate the average value of travel time savings conditional on WTP, a metric that is associated with quantifying travel savings benefits among those who are willing to pay for travel time savings. This conditional metric is useful for segmenting demand to inform the preferences of those actively interested in paying for travel time savings. Third, we calculate the overall VTTS across the population, including accounting for those individuals who are unwilling to pay at all. This last metric is most associated with system-wide cost benefit analysis, providing the aggregate benefit of travel time savings that reflects the time valuations of all users.

Following the mathematical formulation of the model described in Section 3.2, the probability that each individual would be willing to pay at all is calculated using $P(z_q = 1) = \Phi(\gamma'w_q)$. Next, the expected value of the logarithm of the $cVTTS_q$ for a given individual q (denoted by y_q), given that an individual is willing to pay, is given by (see Greene, 2000; page 929)

$$E[y_q | z_q = 1] = \int_{-\infty}^{\infty} v [f_{y_q}(v | z_q = 1)] dv = \beta'x_q + \rho\sigma\lambda(\gamma'w_q), \text{ where } \lambda(\gamma'w_q) = \frac{\phi(\gamma'w_q)}{\Phi(\gamma'w_q)}. \quad (4)$$

Similarly, the variance of the logarithm of $cVTTS_q$, given the willingness to pay, is given by

$$\begin{aligned} VAR[[y_q | z_q = 1]] &= \left(\int_{-\infty}^{\infty} v^2 [f_{y_q}(v | z_q = 1)] dv \right) - \left(\int_{-\infty}^{\infty} v [f_{y_q}(v | z_q = 1)] dv \right)^2 \\ &= \sigma^2 \left[1 - \rho^2 \delta(\gamma'w_q) \right], \text{ where } \delta(\gamma'w_q) = \lambda(\gamma'w_q) [\lambda(\gamma'w_q) + \gamma'w_q] \end{aligned} \quad (5)$$

Using this expected value and variance, the expected $cVTTS_q$ (the second metric) for an individual who is willing to pay is given by

$$E[cVTTS_q | z_q = 1] = \exp \left(E[y_q | z_q = 1] + \frac{1}{2} VAR[y_q | z_q = 1] \right). \quad (6)$$

Next, the overall (unconditional) expected $VTTS_q$ (the third metric) may be computed as:

$$E[VTTS_q] = 0 * P(z_q = 0) + E[cVTTS | z_q = 1] * P(z_q = 1). \quad (7)$$

The three metrics above can be computed for any individual and trip context.⁷ However, because the number of such combinations are substantial even if we consider only the discrete exogenous variables, and there are continuous exogenous variables too, it is impossible to provide such disaggregate values of the three metrics for each individual in a single paper. But, to provide a sense of the variation across individual/household demographics and trip characteristics, we compute the three metrics for each discrete exogenous variable (one at a time) as follows. We first set the state of the exogenous variable to a specific value for every individual in the sample (for instance, setting everyone in the sample as women), while maintaining all other exogenous variables at their original values, and compute the three metrics for each individual. The individual values for each of three metrics are next averaged across all individuals in the sample and reported in Table 3 for the corresponding discrete exogenous variable. We do not consider continuous exogenous variables in Table 3 (related to cost of trip on non-car modes, current trip travel time, proportion of expected travel time saved, and proportion of maximum delay expected to be saved) because the three metrics can be computed at any continuous value for these variables. However, these continuous exogenous variables still feature in the computation of the metrics for the discrete exogenous variables.

The results for the three metrics are presented in Table 3. The first set of numeric values for men indicates that the share of men who would be willing to pay any amount at all is estimated to be 0.812; the expected value of $cVTTS$ conditional on being willing to pay for men is Rs. 972.3 per hour, and the overall expected $VTTS$ for men is Rs. 789.5 per hour. Finally, in addition to calculating these three metrics using the proposed joint model, the same metrics may be calculated using a model that maintains separation between the discrete and continuous components (this is the same independent model used for comparison in Section 4.2). We present the overall $VTTS$ estimate calculated using the independent model in the final column of Table 3. Thus, for men the overall expected $VTTS$ under the independent specification is Rs. 839.4 per hour, an appreciable overestimate relative to the corresponding $VTTS$ from the proposed joint model. Other values in Table 3 may be similarly interpreted. Overall, the comparison demonstrates that ignoring the correlations between the discrete and continuous components yields materially different $VTTS$ estimates. The largest differences across individual and household characteristics occur for income and household composition, while even larger discrepancies arise across travel contexts, particularly by trip type.

In the next few sections, we point out selected implications based on these values for transportation policies, transportation infrastructure improvements, and traffic congestion reduction strategies. In these sections, we focus on WTP and the overall $VTTS$ (the first and third columns in Table 3), not on $cVTTS$ conditional on willingness to pay (the second column in Table 3), though we present this second metric too in Table 3 so readers can see why WTP can be high, but overall $VTTS$ can be low for certain population subgroups and travel contexts. That is, while being more willing to pay to reduce travel time savings, the $cVTTS$ conditional on willingness to pay can be lower for some population groups and some travel contexts.

⁷ The post-estimation $VTTS$ calculations presented in Table 3 were undertaken using specialized code written in the GAUSS programming language. However, such estimates may be computed for any additional combinations of individual and trip context variables using the coefficients provided in Table 2 and off-the-shelf software packages for Heckman-type selection models, such as the *ssmodels* package in R or the *statsmodels* package in Python.

5.2 WTP and VTTS Heterogeneity Across Population Subgroups

As may be observed in the upper panel of Table 3, the valuation of travel time savings varies significantly across demographic groups, implying that the benefits of transportation investments are not evenly distributed. In particular, women, younger individuals, those with low formal education, those not living alone and with no children in the household, and employed individuals exhibit a high WTP and a high VTTS, while adults with children in the household also indicate a high VTTS even if a rather low WTP. This indicates that transportation investments in areas more frequented by these individuals would be beneficial, including improving travel infrastructure around schools and employment centers, as well as considering the addition of carpool lanes that may be used by families with children. Further, emphasizing land-use connectivity for efficient participation in multiple activities in close proximity rather than purely capacity expansions is likely to have significant impacts for families with children who undertake more trip-chaining.

The results also reveal that individuals whose household income is less than 2.5 million rupees have a low WTP, but a higher overall VTTS compared to those with higher incomes. This contrasts with many existing findings suggesting that VTTS generally increases with income (see, for example, Jara-Diaz and Guevara, 2003; Börjesson et al., 2012; Athira et al., 2016; Binsuwadan et al., 2023). However, we should note that even an income of 2.5 million rupees is relatively high in the context of Mumbai, and the sample consists of a relatively small number of low-income individuals who travel using the private modes considered. Thus, this result may reflect the notable freedom that the highest-earning households have in terms of scheduling flexibility and relatively fewer travel constraints compared with others. Still, the results suggest that there is strong interest in reducing travel times even among lower-income individuals, highlighting the significant, growing, and unevenly distributed impacts of traffic congestion in Mumbai (see *Comprehensive Mobility Plan (CMP) for Greater Mumbai*, 2016; Salunke and Bang, 2024). Given the high interest in travel time reduction among lower-income populations as well as equity issues surrounding the introduction of priced lanes, the implementation of income-graduated toll caps or means-tested discount programs (which place an upper limit on the toll cost for low-income individuals or offer tiered discounts based on income level or other measures of hardship) present good options for pricing implementations. These types of income-based programs offer travel time savings for individuals across all income groups without placing an undue burden on lower-income individuals.⁸ Additionally, directing toll revenues to programs benefiting lower-income travelers, including improvements for active transportation infrastructure and public transportation, may help to provide additional high-quality transportation alternatives for these travelers.

5.3 Prioritization of Travel Time Savings by Trip Purposes, Modes, and Times-of-Day

The substantially higher VTTS among those traveling for work/education by car before 9:30 am (relative to other trip purpose-mode-time of day combinations), as reflected in the lower panel of Table 3 labeled “Trip Characteristics,” highlights the importance of prioritizing work/education trips during peak periods in congestion mitigation efforts. Focusing on infrastructure development and road pricing (both flat tolling and congestion pricing) in areas with high employment densities, and corridors used extensively for car commutes, is likely to provide the highest return on

⁸ Of course, with these types of programs, implementation challenges exist by way of determining eligibility. One possibility is to link individuals to existing social-assistance programs to reduce administrative requirements. Further, using automatic digital payment systems can reduce complexity for program participants by automatically applying fare reductions (see Paleti et al., 2016).

investment. Besides, the high traffic volumes through these corridors during the morning peak period implies that travel time savings during this period will be magnified across a relatively large user base. Further, a significantly reduced VTTS at off-peak times compared to the morning peak across all modes and trip purposes indicates that congestion mitigation and pricing efforts should be time sensitive. In terms of priced lanes, dynamic pricing strategies that raise prices during peak hours while reducing or eliminating prices at off-peak hours, would be beneficial given these large variations in VTTS across different times of the day.

Although the total VTTS is lower for those traveling for maintenance and leisure purposes, a high willingness to pay for travel time savings, particularly during the morning peak, for such trips suggests that maintenance/leisure trip purposes are also good targets for travel investments. This increased level of perceived acceptability of payments for travel time reductions would be missed if only the overall VTTS were considered, highlighting the importance of directly considering WTP too. Thus, while large-scale pricing efforts that impose high costs are likely to be unpopular among those traveling for these trip purposes, there is support for smaller scale efforts to reduce travel time even for these purposes. Such targeted improvements at local commercial centers could include (a) strategic parking policies that provide higher cost parking options closer to population commercial destinations, (b) dynamic parking information systems that reduce search time, (c) curb space allocation for pickup/dropoff locations for ridehailing, taxi, and autorickshaw users to help facilitate access even if at a premium cost, and (d) land-use strategies that co-locate maintenance/leisure activity locations with other services.

5.4 WTP and VTTS Variations Based on Trip Sharing and Trip Frequency

Although we find that the total VTTS is lower for those taking shared trips, there is a relatively high WTP among those who are sharing. This finding suggests that tolling and congestion pricing should not be limited to single-occupancy vehicles, as shared travelers also derive meaningful benefits from reduced delays and appear willing to pay for these travel time reductions. This contrasts with many existing roadway policies that effectively provide complimentary travel time savings for high-occupancy vehicle users (see, for example, Cohen et al., 2022). At the same time, the relatively lower total VTTS among those sharing rides does suggest that discounts are warranted, potentially including tiered pricing levels based on the number of occupants. From an efficiency perspective, congestion prices that more closely reflect group-specific valuation of time can better align marginal willingness to pay with marginal social cost, while still preserving the policy objective of encouraging shared travel. Such policies would continue to promote ride-sharing, while extending congestion management strategies and revenue generation to shared trips in a manner consistent with the lower monetary valuation placed on these trips.

Further, given that frequent travelers seem more reluctant to pay for travel time savings (as evidenced by a slightly lower, though still above 80%, share of frequent travelers willing to pay for travel time savings as well as the lower VTTS among this group), policies that provide discounts to high-frequency travelers may also be beneficial. These types of tiered loyalty programs avoid the imposition of exorbitant costs on routine travelers and ensure that recurring mandatory trips (such as for work or education) remain affordable even as congestion pricing is applied. This approach is especially important for travelers with limited alternatives, who may otherwise face disproportionately high cumulative toll costs over time. Such loyalty programs have not been commonly implemented, though examples include the Central Florida E-PASS Customer Loyalty Program (which provides a monthly discount of 5-10% for high-volume users; see Central Florida Expressway Authority, 2016) and the Japan Electronic Toll Collection System (which

provides a commuter discount of up to 50% during peak hours for those making at least 10 trips per month; see Japan ETCcard, 2025). Overall, these types of flexible pricing policies balance the need to implement congestion management programs with the needs of different groups of travelers, highlighting the importance of considering both WTP and $cVTTS$ and identifying variations in each across different travel contexts. While WTP and $cVTTS$ are positively correlated, they capture distinct dimensions of heterogeneity: the mass of individuals with zero (or effectively zero) WTP determines the participation group, while variation in $cVTTS$ across those willing to pay governs the intensive margin. Disaggregating these two dimensions allows policymakers to map how both the concentration of zero WTP and the distribution of VTTS vary across segments. Without understanding both who is willing to pay at all and how much different segments value time, policymakers cannot effectively calibrate differentiated pricing schemes, anticipate responsiveness across contexts, or evaluate potential equity and revenue implications. Thus, treating VTTS as a single homogeneous parameter risks obscuring meaningful distribution patterns that are directly relevant for pricing design and policy evaluation.

6. CONCLUSIONS

Accurate VTTS estimates by socio-demographic groupings and travel contexts are important for a variety of policy decisions in the transportation sector. In this paper, we use a contingent valuation based iterative bidding method to directly elicit both willingness to pay (WTP) and a continuous measure of VTTS for those with a positive WTP, employing information elicited from a sample of individuals residing in Mumbai, India. Through this data collection exercise, we are able to quantify WTP and overall VTTS variations across population subgroups and travel contexts. The findings reveal significant heterogeneity in both WTP and overall VTTS across sociodemographic groups. In terms of the travel context, WTP and VTTS are highest (and by a large margin) for work and education trips taken by car during the morning peak period. Young individuals, those not living alone, and those traveling infrequently also exhibit both high WTP and high VTTS. In contrast, WTP and VTTS are not always aligned perfectly. Thus, in some contexts, individuals display a generally elevated WTP, but a relatively low VTTS (such as for shared trips and maintenance/leisure trips after 9:30 am), while in other cases, individuals exhibit low WTP but high VTTS (such as adults with children in the household, and those from low income households). These differences underscore the importance of separating the discrete and continuous components of the value of travel time savings, providing strategic insights for targeted investments that align with the different perceptions of travel time savings for different trips as well as directly considering how benefits from travel time savings are distributed across the population, as discussed in detail in the previous section.

By explicitly separating the discrete and continuous VTTS components, the current framework provides planners with a more behaviorally realistic basis for predicting adoption of priced facilities, estimating revenue potential, and assessing elasticities under different pricing levels. Incorporating the mass of individuals with zero VTTS is particularly important for forecasting, because these travelers will not switch to priced lanes regardless of pricing levels, impacting overall estimates of diversion onto these priced lanes as well as the distribution of benefits that these types of projects may yield. At the same time, the ability of this model to reveal systematic heterogeneity based on both individual characteristics and travel context provides insights for appraisal studies by generating a broad set of segment-specific VTTS values than is typically available through differentiation by mode, purpose, and income. By mapping how the VTTS distribution varies across sociodemographic groups and travel contexts, the model supports

a detailed cost-benefit analysis regarding the monetization of time savings, the evaluation of the overall impacts of transportation projects, and an improved assessment of the distribution of transportation project benefits across population subgroups. Overall, the methodology in this study offers planners and policymakers a rich tool for designing, evaluating, and calibrating equitable transportation policies and investments.

Based on our findings, future research efforts should directly consider the possibility that some individuals are unwilling to pay for travel time savings and explore the impacts of this issue on existing measures of VTTS as imputed using traditional methods. This includes more closely examining psychological issues surrounding willingness to pay for priced lanes or feelings of fairness regarding congestion pricing as well as examining real-world pricing contexts to determine why some individuals never choose priced lanes when cost/time tradeoff exists. In fact, this issue may have even larger effects in areas where there is generally more pushback against transportation pricing strategies. Further, while the current study focused on the context of pricing related to private motorized individual travel, exploring WTP and VTTS in the context of non-motorized transport modes as well as public transportation would provide additional insights into investments across the transportation sector. Similarly, while the trips considered in the current study were heavily clustered during the morning peak (preventing a detailed consideration of VTTS variations across finer time-of-day intervals), future research should explore time-of-day variations in VTTS to inform time-sensitive dynamic pricing and congestion management strategies that respond both to roadway conditions and to temporal variation in travel time valuations.

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Table 1: Descriptive Statistics of Exogenous Variables

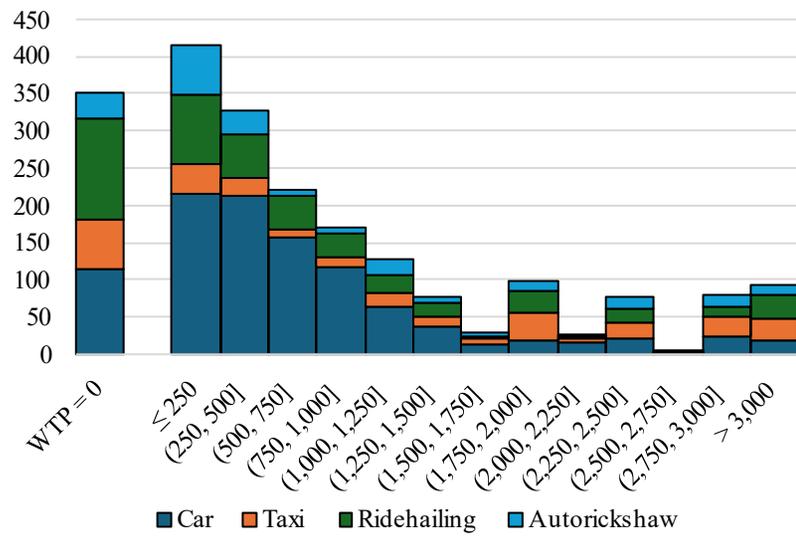
<i>Individual Characteristics</i>					
Variable	Number	Percent	Variable	Number	Percent
Gender			Education		
Male	816	38.91	Less than senior secondary	271	12.92
Female	1281	61.09	Senior secondary passed	706	33.67
Age			Bachelor's degree	1008	48.07
Less than 25	207	9.87	Graduate degree	112	5.34
25-34	877	41.82	Employment		
35-44	550	26.23	Employed	1281	61.09
45-54	344	16.41	Not currently employed	816	38.91
55 or older	119	5.67			
<i>Household Characteristics</i>					
Variable	Number	Percent	Variable	Number	Percent
Lives Alone			Presence of Children (<18 Years of age)		
Yes	124	5.91	Yes	1334	63.61
No	1973	94.09	No	763	36.39
Household Income (million rupees)			Residential Neighborhood Population Density		
Less than 1.0	671	32.00	Low	656	31.28
2.0 - 2.5	1040	49.59	Medium	675	32.19
2.5 or more	386	18.41	High	766	36.53
<i>Trip Characteristics</i>					
Variable	Number	Percent	Variable	Number	Percent
Mode			Trip Distance (kilometers)		
Car	1031	49.17	Less than 5.00	370	17.64
Rickshaw	503	23.99	5.00 - 9.99	741	35.34
Ridehailing	245	11.68	10.00 - 19.99	656	31.28
Taxi	318	15.16	20.00 or more	330	15.74
Trip Purpose			Trip Frequency		
Work	1328	63.33	Once per week	573	27.32
Maintenance	372	17.74	2 - 4 days per week	791	37.72
Education	104	4.96	5+ days per week	733	34.96
Leisure	293	13.97	Time of Day		
Cost (Rupees)			Before 9:30am	948	45.21
Less than 100	377	17.98	9:30am - 12:00pm	643	30.66
100 - 199	352	16.78	After 12:00pm	506	24.13
200 - 299	179	8.54	Shared Trip		
300 or more	158	7.53	Yes	955	45.54
NA (cars)	1031	49.17	No	1142	54.46
Variable			Mean	Standard Deviation	
Expected Travel Time (hours)			0.65	0.31	
Congested Travel Time (hours)			1.18	0.50	
Free Flow Travel Time (hours)			0.33	0.16	
Proportion of Expected Travel Time Saved			0.48	0.14	
Proportion of Maximum Delay Expected to be Reduced			0.38	0.14	

Table 2: Model Results

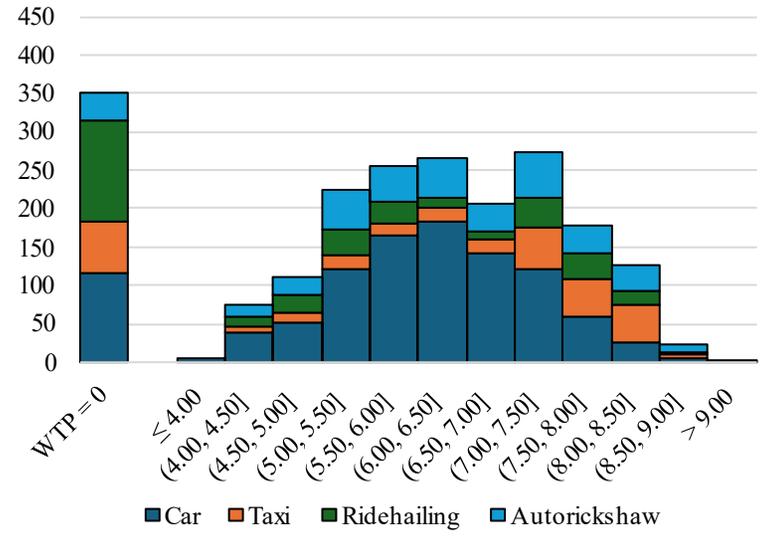
Variable (base)	WTP		LN(<i>cVTTS</i>)	
	Coeff.	t-stat	Coeff.	t-stat
<i>Individual and Household Characteristics</i>				
Gender (male)				
Female * Work or Education Trips	0.19	2.07	0.17	2.49
Female * Maintenance or Leisure Trips	0.19	2.07	-0.12	-1.40
Age (less than 34)				
35-44 * Work or Education Trips	-0.41	-4.02	-0.27	-4.87
45 or older * Work or Education Trips	-0.70	-6.41	-0.27	-4.87
Education (less than senior secondary)				
Senior Secondary passed	-0.40	-2.81	-0.11	-1.68
Bachelor's degree or higher	-0.47	-3.26	-0.38	-5.39
Income (less than Rs. 25 Lakh)				
25+ * Work or Education Trips	0.32	2.51	-0.31	-4.30
25+ * Maintenance or Leisure Trips	0.32	2.51	0.34	2.90
Household Composition (multiple adults with no children)				
Presence of Children * Work or Education Trips	-0.57	-5.49	0.58	9.30
Presence of Children * Maintenance or Leisure Trips	0.23	1.68	0.23	2.67
Lives Alone	-0.33	-2.05	-0.59	-5.71
Employment (not employed)				
Employed * Work or Education Trips	0.23	2.10	0.25	3.56
Population density (low or medium)				
High	-0.46	-5.64	0.19	3.36
<i>Trip Characteristics</i>				
Trip Type (Maintenance or Leisure by Car after 9:30 am)				
Work or Education by Car before 9:30 am	1.43	9.60	0.96	6.61
Work or Education by Car after 9:30 am	--	--	0.58	4.15
Work or Education by non-Car before 9:30 am	0.86	7.51	0.44	3.17
Work or Education by non-Car after 9:30 am	--	--	0.44	3.17
Maintenance or Leisure by Car before 9:30 am	0.49	1.84	--	--
Maintenance or Leisure by non-Car before 9:30 am	0.49	1.84	0.63	6.28
Maintenance or Leisure by non-Car after 9:30 am	--	--	0.63	6.28
Shared Trip (not shared)				
Shared	0.21	2.13	-0.39	-8.16
Trip Frequency (1 day per week)				
2+ days per week	-0.66	-5.87	-0.33	-5.50
Cost (thousand Rs.)	-0.73	-1.80	-0.72	-2.34
Time (hours)	0.39	2.40	-1.35	-16.33
Portion of Travel Time Saved	1.61	5.56	-0.96	-5.24
Portion of Maximum Delay Expected to be Saved	-2.03	-6.20	-1.09	-5.38
<i>Constant</i>	1.58	6.69	7.87	57.80
<i>Correlation and Scale (standard deviation)</i>				
WTP	1.00	--	--	--
LN(<i>cVTTS</i>)	0.31	11.14	0.79	35.29
Measures of Fit			Proposed Model	Independent Model
Log-Likelihood at Convergence			-2750.51	-2766.03
Log-Likelihood at Constants			-3630.35	-3630.35
Number of Parameters			52	51
Adjusted Likelihood Ratio Index			0.229	0.225
Bayesian Information Criterion			2836.87	2850.73
Likelihood Ratio Test			31.04	

Table 3: Variation in Value of Travel Time Savings by Exogenous Characteristics

		Proposed Model			Independent Model VTTS
		WTP	<i>c</i> VTTS	VTTS	
Baseline		0.834	1061.2	885.0	887.2
<i>Individual and Household Characteristics</i>					
Gender	Male	0.812	972.3	789.5	839.4
	Female	0.847	1051.9	890.9	843.3
Age	Less than 25	0.873	1143.2	998.0	985.0
	55 or older	0.771	974.6	751.4	776.1
Educational Attainment	Less than senior secondary	0.894	1311.4	1172.4	1170.9
	Graduate degree	0.819	918.5	752.2	757.3
Household Income	Less than 2.5 million rupees	0.823	1105.1	909.5	879.8
	2.5 million rupees or more	0.876	874.9	766.4	928.7
Presence of Children	Yes	0.807	1232.4	994.6	956.9
	No	0.871	741.3	645.7	726.3
Lives Alone	Yes	0.772	614.2	474.2	579.1
	No	0.837	1084.2	907.5	903.7
Employment	Employed	0.841	1092.5	918.8	926.7
	Not currently employed	0.809	919.6	743.9	724.0
Population Density	Low	0.868	1014.0	880.1	889.8
	High	0.781	1140.7	890.9	893.1
<i>Trip Characteristics</i>					
Trip Type	Work or Education by Car before 9:30 am	0.948	2466.6	2338.3	1817.7
	Work or Education by Car after 9:30 am	0.666	699.3	465.7	590.6
	Work or Education by non-Car before 9:30 am	0.874	925.7	809.0	965.6
	Work or Education by non-Car after 9:30 am	0.666	991.4	660.3	750.5
	Maintenance or Leisure by Car before 9:30 am	0.921	422.1	388.7	493.1
	Maintenance or Leisure by Car after 9:30 am	0.837	432.5	362.0	462.8
	Maintenance or Leisure by non-Car before 9:30 am	0.921	727.7	670.2	768.4
	Maintenance or Leisure by non-Car after 9:30 am	0.837	745.2	623.7	719.4
Shared Trip	Shared	0.855	816.0	697.7	823.9
	Not Shared	0.818	1217.4	995.8	923.3
Frequency	1 day per week	0.912	1310.6	1195.3	1071.1
	5+ days per week	0.803	979.6	786.6	812.1



(a) Value of Travel Time Savings



(b) log (Value of Travel Time Savings)

Figure 1: Distribution of Willingness to Pay and Values of Travel Time Savings