AN EXPERIMENT IN MEGA-REGIONAL ROAD PRICING USING ADVANCED COMMUTER BEHAVIOR ANALYSIS

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ABSTRACT

Worsening highway congestion is a challenge to mega-regional competitiveness; and changing regional geographies and development location decisions, among other factors, demand that public policy responses go beyond traditional demand management approaches. Congestion pricing has been suggested as a remedy. In this article, we analyze the outcomes of multiple congestion pricing approaches for the Capital Mega-region that spans the following five Metropolitan Planning Organization regions: Washington (DC-MD-VA), Baltimore (MD), Wilmington (DE), Fredericksburg (VA), and Frederick (MD) and counties in adjoining states of NJ, PA and WV. Using a mega-regional travel demand model, we incorporate different values-of-time for travelers under different conditions. However, our value-of-time estimates are not limited to income categories. Our estimates also include trip purposes across a number of scenarios. We demonstrate that adding trip-purpose to congestion price determination leads to different outcomes at the mega-regional level and also for individual sub-regions. We conclude with implications for adopting this approach and ideas for implementing them in a complex institutional set-up.

Keywords**:** value of time, elasticity, commuter travel, congestion pricing, megaregion

INTRODUCTION

The right scale for transportation planning has been a subject of considerable analysis. For example, a number of studies have shown the limitations of traditional Metropolitan Planning Organization (MPO)-level decisions in addressing larger regional issues (Amekudzi et al. 2007, Barbour and Teitz 2006, Bollens 1997, Wheeler 2009 and Wheeler 2002). They range from difficulties in accounting for extra-territorial spillovers (Bento et al. 2009 and Downs 1994), setting boundaries amidst shifting economic geographies (Dewar and Epstein 2007) and the institutional complexities of formulating and implementing coherent supra-regional policies (Friedmann and Weaver 1979, Katz 2000, Teitz and Barbour 2007, and Womersley 2006). With the emergence of mega-regional clusters as engines of economic growth and competitiveness, planners, policymakers and researchers need to consider how transportation systems can aid regional development, mitigate the challenges resulting from shifting regional travel demands, and facilitate robust decision-making that can withstand future uncertainties.

One such challenge is transportation related congestion. With the decentralization of employment in the last two decades and increased suburb-to-suburb trips, congestion has become a spatially broader issue (Ewing and Cervero 2001 and Orfield 2002). In many metropolitan areas, severe highway congestion problems are expected to exacerbate if the current trends continue (Cervero 2003, Downs 2004 and TRB 2009) This has implications for mega-regional competitiveness and thus congestion mitigation approaches and their mega-regional outcomes deserve closer attention (Keil and Young 2008).

So far, tolls and occupancy controls have been the most commonly used instruments for regulating highway use. However, with better modeling techniques and improvements in Intelligent Transportation Systems, more real-time, demand-driven *congestion* pricing approaches are being considered (Giuliano 1992). While congestion pricing shares many common characteristics with traditional toll assessment, its potentially dynamic nature and focus on congestion mitigation over infrastructure financing, offer new opportunities and challenges.

Apart from political and institutional complexities, a host of factors go into congestion price analysis including, travel demand, infrastructure supply, and commuting patterns, A central tenant of this process is commuter behavior, i.e. the elasticity of travel demand with respect to congestion and price. Travelers may elect to pay a cost based on whether there is a corresponding time savings, convenience or available alternative modes or routes. A key parameter in this analysis is the estimated value of time (VOT). The VOT literature has traditionally focused on income distribution among all trips (Hensher 2001 and Lisco 1968). However, extending the notion of VOT using travel demand models to include trip purpose has the potential to enrich VOT based analysis. It can also add a more explicit spatial component to the analysis thus allowing us to test pricing approaches at large scales. This is what we do in this paper. Specifically, we ask 1) whether congestion pricing determination can be improved using an enhanced Value-of-Time determination approach that accounts for both income and trip-purpose of the commuters, 2) how mega-regional pricing approaches using congestion pricing differs in outcome from traditional MPO based approaches and 3) how different conditions in future can affect the congestion outcomes differently under traditional MPO-based or mega-regional approaches.

We use the *Capital Megaregion* to demonstrate the value of our approach. We define this mega-region to span the following five Metropolitan Planning Organization (MPO) regions: Washington (DC-MD-VA), Baltimore (MD), Wilmington (DE), Fredericksburg (VA), and Frederick (MD). In addition, the mega-region includes a number of counties adjoining the above regions including those in southern New Jersey and Pennsylvania and northeastern West Virginia. The unifying characteristics for this mega-region besides commute-shed linkages are the presence of a large number of federal and other government-related jobs and environmental systems connectivity, especially at the watershed level.

We proceed as follows. In the next section, we discuss the practices and research on how value-of-time is incorporated in travel behavior models and what that tells us about congestion pricing and issues of scale. In the following section, we establish our framework to develop and analyze mega-regional scenarios. This process involves the use of multi-level transportation models that are sensitive to congestion pricing and variations in future travel demand. Next, we generate estimates of VOT using different approaches viz. income only, income and trip purpose, and income and trip purpose and variable travel demand; using an example problem on a small network, we demonstrate the value of using trip-purpose in VOT estimation. In the following section, we present the results of applying this approach on our case study: the Capital Mega-region. We conclude with specific implications for mega-regional decision-making.

LITERATURE REVIEW

In this section, we look at the literature on approaches used for analyzing commuter and non-commuter travel behavior using differential VOT, further cross-classified by income and trip purpose. We then look at their limitations to establish a foundation for our work. Finally we draw evidence from existing research on how these approaches can aid mega-regional decision-making.

From the early 1990s, a series of projects in the United States has demonstrated the applicability of congestion pricing. Many transportation projects have combined pricing with priority for high-occupancy vehicles in the form of “High Occupancy Vehicle (HOV) and High Occupancy Toll (HOT)” lanes. In this scheme, a set of express lanes on an otherwise free and congested road offers high-quality service to people who are willing to pay a time-varying toll and/or who ride in carpools. These projects provide an opportunity to study some behavioral parameters that are central to the evaluation of transportation projects. The most important is the VOT, i.e. the marginal rate of substitution of travel time for money, which measures willingness to pay for reductions in the day-to-day variability of travel times facing a particular type of trip (Small and Yan 2001). A commuter traveling between any origin and destination points can pay higher tolls to save on travel time, or use alternative routes and/or modes to avoid tolls but travel for a longer time. In theory, the right toll can reduce peak hour congestion; thus, travelers who highly value time and who want to travel at peak periods can shift to toll roads. The relationship between toll, and travel time can raise a fundamental question regarding the travelers’ willingness to pay so as to save travel time, i.e., commuters’ value of travel time.

The concept of VOT and travel behavior has been researched extensively. In the early applications of 1960, the notion of value of time was used to develop the theory of time allocation and in practice to estimate, say, the time savings in cost-benefit analysis of highway investment decisions (Warner 1962; Lisco 1967 and Thomas, 1967). With advances in theory, particularly random utility theory, and methodologies, especially discreet choice models, and improvement in computing, the VOT literature has shifted to focus on individual behavior. Small (1982) generalized from a review of many estimates that the average VOT for journeys to work is about 50% of the gross wage rate. In most studies since then, VOT of commuters have been developed using discrete choice models (e.g., binary logit, mixed logit, multinomial logit, and nested logit) and based on traveler survey data (Small and Rosen 1981; Leurent and Wagner

2009; Sullivan 2002; Hultkrantz and Mortazavi 2001; Brownstone et al. 2003; Cirillo and Axhausen 2006; Brownstone and Small 20005).

While the above approaches provide a useful framework for estimating congestion pricing, they have several limitations. Generalized measures of VOT are inherently regressive in nature and may lead to inequitable distribution of costs and benefits among users (Mackie et al. 2001). Extending the characterization of VOT to include income groups (Hensher 2001; Gunn 2001) addresses this to an extent, although congestion pricing remains regressive, adding fuel to the political opposition to many such measures. Another limitation of this approach is the lack of emphasis on travel behavior in VOT estimation. To address this Jara-Diaz (2003) suggested extending the concept from using one VOT for all non-work activities to using specific value for each activity. Activity-based estimates promise to advance the value of VOT and associate it with longer distance commutes and interregional travel.

Travel demand models can be useful in this regard. Unlike travel surveys and econometric models that provide commuters' willingness to pay, travel demand models can provide useful information on travel behavior and, by extension, connect it with VOT. The sensitiveness of VOT in such models can vary across two dimensions; income category and trip purpose. For example, a commuter during the peak period may be willing to pay more than a non-commuter. If so, when a non-toll road is converted to a toll road, the marginal rate of substitution for the commuters can be expected to be lower than that of the non-commuter. These impacts are similar in effect with income-based categorization where the marginal rate of substitution for a high-income traveler will likely be lower than that of lower income traveler. In practice however, it is a combination of these effects but their implications are not very clearly studied in the literature. This, as we demonstrate later, presents a gap in mega-regional congestion pricing that this research attempts to address.

In summary, the notion of value of time has become central to transportation economics, modeling and policy. It allows us to incorporate the time dimension of travel into capital decisions and use pricing mechanisms to influence behavior. In this section, we synthesized the established literature on how value-of-time is estimated and how it affects congestion price determination. We find that income-only approaches provide limited estimate of the value-of-time and factoring trip-purpose in such estimation can be a more robust approach. Due to the role of value-of-time in congestion price determination and the promise of congestion pricing in mega-regional transportation planning, analyzing these issues at such scales can illuminate possible efficiencies.

METHODOLOGY

Effective modeling efforts have in the past focused on incorporating road pricing into the highway assignment algorithm via Waldrop's User Equilibrium (UE) objective function and a

Frank-Wolf (FW) solution approach. In the mega-regional context travel behavior, especially route choice can be studied with the user equilibrium method. A set of models are proposed in Table 1 and described in the following paragraphs.

A base-case, which represents the current mega-regional conditions, without any pricing, is analyzed using user-equilibrium. In Table 1, the objective function of the Base-case shows assignment of flows occur as per Wardrop's first principle, which denotes that “no user can experience a lower travel time by unilaterally changing routes” (Sheffi 1985). In simple terms, the equilibrium is achieved when the travel cost on all used paths is equal. The three terms in equation (1) represent the total travel cost. The first term, t_a, is the travel time for link a, which is a function of link flow x_a. The sum of these two terms in equation (1) can be referred as user cost for link a ($u_a = t_a(x_a)$). Equation (2) is a flow conservation constraint to ensure that flow on all paths *r*, connecting each Origin-Destination (O-D) pair (*i*-*j*) is equal to the corresponding demand. In other words, all O-D trips must be assigned to the network. Equation (3) represents the definitional relationship of link flow from path flows.

Table 1: Summary of Proposed Models

Model	Objective Function	Constraints
Base-case	$Minimize\ \sum_a \int_0^{x_a} t_a(x_a)$ (1)	$\sum_r f_{ij}^r = q_{ij}$ (2) $x_a = \sum_i \sum_j \sum_r f_{ij}^r \, \delta_{a,ij}^r$ (3) $f_{ij}^r, q_{ij}^r \geq 0$ (4)
Model-1	$Minimize\ \sum_a \int_0^{x_a} \left(t_a(x_a) + \frac{\tau_a}{\gamma_i}\right)$ (6)	
Model-2	$Minimize\ \sum_a \int_0^{x_a} \left(t_a(x_a) + \frac{\tau_a}{\gamma_i^p}\right)$ (7)	
Model-3	$Minimize\ \sum_a \int_0^{x_a} \left(t_a(x_a) + \frac{\tau_a}{\gamma_i^p}\right) - \sum_{ij} \int_0^{q_{ij}} D_{ij}^{-1}(\,x_a)$ (8)	

Equation (4) is a non-negativity constraint for flow and demand. The travel time function $t_a(.)$ is specific to a given link ‘a’ and the most widely used model is the Bureau of Public Roads (BPR) function given by

$$t_a(x_a) = t_o\left(1 + \alpha_a \left(\frac{x_a}{C_a}\right)\right)^{\beta_a} \quad (5)$$

where $t_o(.)$ is free flow time on link ‘a’, and α_a and β_a are constants (and vary by facility type). C_a is the capacity for link a. In the Base-case the objective is the minimization of user travel time. In this Base-case, the multiclass UE assignment considers VOT for each by income but not trip purpose.

Model-1 is distinguished from the Base-case with the implementation of congestion pricing on specific links. Like the Base-case a unique VOT is specified for each income class, but does not vary by trip purpose. Specification of a VOT for each income class means the perceived toll values vary for users by income class. In general practice, toll values are modeled to reflect varying values-of-time. This can be achieved in each model by adding a term for the toll value scaled by the corresponding VOT by income to the objective function shown in Equation (1). The revised equation reflects this change, and is shown in Equation (6).

While the objective function in Model-1 (equation-6) is changed compared to the Base-case (equation-1), the equilibrium constraints remain the same. The Base-case model is not suited for congestion pricing analysis, but the Model-1 is capable of doing so where VOT varies by income category.

Often, a traveler's VOT varies depending on the type of trip that is being considered. For example, when a trip is being made for the purpose of commuting to work, the value of time is higher than a trip that is made for shopping or recreational purposes. The objective function for Model-2 shown in Equation (7) incorporates this principle. The second term, ($\frac{\tau_a(x_a)}{\gamma_i^p}$) represents the cost of travel for toll value of τ_a and is weighted with VOT by income group *i*, and purpose *p* (γ_i^p).

Model-3 builds on the income and purpose classified VOT in Model-2 but adds inverse demand based highway assignment. Link (Model-1) and purpose differentiated pricing (Model-2) provide a good understanding of shifting routes and modes (discussed later in the paper). However, both Model-1 and Model-2 do not consider the variability of demand because of changes in network conditions as a result of changes in link pricing. Alternatively, highway users are not elastic to the pricing strategy. Demand elasticity can be incorporated into the models by introducing an inverse demand function in the objective function. Modeling variable demand completely changes the objective function.

This formulation of variable demand allows the decision maker to model the elasticity of the user behavior. The constraints for the variable demand model remain the same as in the Base-case (see equations 2-4). The inverse demand function $D_{ij}^{-1}(.)$ is associated with O-D pair *i-j*. An exponential demand function is then used which is a function of potential demand and least user cost paths to determine the new demand $d_{ij}^{\varphi}(x_{ij})$ between O-D pairs is given by

$$d_{ij}^{\varphi}(x_{ij}) = \hat{d}_{ij}^{\varphi}\exp(-\omega * u_{ij}^{c}) \;\forall\; i, j, \tau \qquad (9)$$

where $\hat{d}_{ij}^{\varphi}$ is the potential demand between i-j, u_{ij}^{c} is the least cost path between O-D pairs i-j and ω is a positive constant. This new demand is then fed back into the highway assignment model. The users in the i-j O-D pair are now elastic to the cost of travel (u_{ij}^{c}). Alternatively, as the cost increases the willingness to travel decreases.

Measures of User Response to Pricing

We construct a two dimensional framework to analyze traveler response to congestion pricing. The first dimension is an economic approach that measures travel demand response to changes in road price. The second dimension of analysis measures changes in network conditions as a result of pricing, utilizing measures commonly reported in a traffic demand modeling context.

Price Elasticity of Demand

To analyze the likely travel behavior response to pricing mechanisms in the mega-regional context, we use an analytical framework common in economics to measure change in both an example problem and case study. Our framework is based on price elasticity of demand, where the change in quantity of a good demanded (in this case, travel on a given highway link) is measured relative to the change in the price of that good. Measuring behavioral change in this way allows planners and policy makers to determine how several important components of traveler response to road pricing are affected, including likely traffic volume, impact on each income group, response by users with different trip purposes and possible revenue from pricing.

Determination of price elasticity of demand in a mega-region in our paper is aided by the application of the previously discussed models to an existing validated multistate transportation demand model. Using an existing validated model allows us to change the price of travel in multiple metropolitan areas (each with their own unique characteristics) to determine how drivers will likely react to the pricing, based on income and trip purpose. These changes model probabilistic demand elasticity to road pricing.

We use the arc elasticity formula to model user response. Arc elasticity, using the midpoint formula is simply:

$$E_d = \frac{V_1 - V_0}{\left(\frac{V_0 + V_1}{2}\right)} \div \frac{P_1 - P_0}{\left(\frac{P_0 + P_1}{2}\right)} \tag{12}$$

where P_0 is the initial toll price on the set of city links, P_1 is the new price with the VMT based toll, V_0 is the original volume on all tolled links in the designated area and V_1 is the volume after the VMT toll is initiated. The resulting elasticities provide a measure of traveler sensitivity to road pricing within multiple metropolitan areas and for two key user characteristics: income and trip purpose.

There are five types of elasticity. Where E_d is equal to 0, the user response in demand to price change is known as perfectly inelastic; where users do not change the quantity demanded when the price changes. Second is perfect elastic demand, when E_d is equal to (negative) infinity, users are perfectly elastic. This means that a tiny change in price will drive a large change in demand. Third is when E_d is equal to one, this is called unit elasticity, where change in demand is exactly proportional to the change in price. The final two elasticities are termed elastic demand when E_d is greater than one and inelastic demand when E_d is less than one. Elastic demand means that there is a proportionally greater change in quantity demand than the change in price while inelastic demand means there was a proportionally greater change in price than quantity demanded.

Other Network Statistics

Another common and useful measure of user response to road pricing is the amount of travel in a given area, measured by link travel volume and link distance, known as vehicle miles travelled (VMT). Another measure is the time a road user spends driving, which is the time in hours it takes all road users to reach their destination, or vehicle hour travelled (VHT). Finally, the miles of road where the amount of traffic volume on a given link as a ratio of the link's capacity exceeds .75 is an indicator of network conditions called congested lane mile (CLM). Each of these measures is reported for the case study.

SOLUTION APPROACH

The recently conducted Household Travel Survey (HTS) in the Washington-Baltimore region was used to determine VOT. Five income groups are considered from the survey and presented in Table 2. The value of time in cents per minute and dollars per hour used for each category is presented in the fourth and fifth column. The dollars per hour income is converted to dollars per year by assuming 2080 working hours per year.

Table 2 Value of Travel Time

Income Group	Lower Bound ($)	Upper Bound ($)	cents/minute	$/Hour	$/Year
Income Group 1	0	20,000	8.40	5.04	10,483
Income Group 2	20,001	40,000	25.00	15.00	31,200
Income Group 3	40,001	60,000	41.70	25.02	52,042
Income Group 4	60,001	100,000	50.40	30.24	62,899
Income Group 5	100,001	Higher	106.40	63.84	132,787

Link costs are further categorized by purpose, type of travel and user class. There are 18 trip purposes when classified by income. The trip purposes are classified as Home Based Work (HBW), Home Based Shopping (HBS), and Home Based Other (HBO), each classified in five income categories (i.e. 3*5 = 15 purposes); and journey at work (JAW), journey to work (JTW), and non-home based (3 purposes). Further the five long distance trips: commercial, medium truck, heavy truck, regional auto and regional truck are included in the trips.

The trip purposes are classified as commuter, non-commuter, and regional based on their travel objective. HBW and JAW are considered as a commuter trip, while as HBS, HBO, JTW, and NHB are considered as non-commuter trip. Modes are single occupancy vehicle (SOV), high occupancy vehicle (HOV) with 2 occupants, and HOV with 3 or more occupants. The VOT for different trip purpose, income category and vehicle class is presented in Table 3. For instance, "cost a1" is the value of travel time for income group 1 for HBW trip purpose, and "cost a2" is the VOT for income category 2 for HBO and HBS trip purpose. Further, HBW is classified as commuters, where as HBS, and HBO are classified as "non-commuters". JTW is considered as a commuter trip purpose ("cost c1"), and the average income is considered for JTW. JAW and NHB trip purposes are considered as non-commuter trip purpose with average income ("cost c2"). A total of 20 user classes are defined, which are further categorized as three trip purposes such as commuter, non-commuter and regional. The regional trips are external trips long distance commercial vehicle, auto and truck trips. All the regional trips are considered as higher income category with non-commuter trip purpose ("cost e2").

Table 3 Value of time by income, trip purpose, and user class

Sl. No	User Class	Trip Purpose	Income	Travel Type	Auto Type	VOT
1	1	Home Based Work	Income 1	Commuter	SOV, HOV-2, HOV-3+	cost a1
2	2		Income 2	Commuter	SOV, HOV-2, HOV-3+	cost b1
3	3		Income 3	Commuter	SOV, HOV-2, HOV-3+	cost c1
4	4		Income 4	Commuter	SOV, HOV-2, HOV-3+	cost d1
5	5		Income 5	Commuter	SOV, HOV-2, HOV-3+	cost e1
6	6	Home Based Shopping	Income 1	Non-Commuter	SOV, HOV-2, HOV-3+	cost a2
7	7		Income 2	Non-Commuter	SOV, HOV-2, HOV-3+	cost b2
8	8		Income 3	Non-Commuter	SOV, HOV-2, HOV-3+	cost c2
9	9		Income 4	Non-Commuter	SOV, HOV-2, HOV-3+	cost d2
10	10		Income 5	Non-Commuter	SOV, HOV-2, HOV-3+	cost e2
11	11	Home Based Other	Income 1	Non-Commuter	SOV, HOV-2, HOV-3+	cost a2
12	12		Income 2	Non-Commuter	SOV, HOV-2, HOV-3+	cost b2
13	13		Income 3	Non-Commuter	SOV, HOV-2, HOV-3+	cost c2
14	14		Income 4	Non-Commuter	SOV, HOV-2, HOV-3+	cost d2
15	15		Income 5	Non-Commuter	SOV, HOV-2, HOV-3+	cost e2
16	3	Journey to Work*	All	Commuter	SOV, HOV-2, HOV-3+	cost c1
17	8	Journey at Work**	All	Non-Commuter	SOV, HOV-2, HOV-3+	cost c2
18	8	Non Home Based**	All	Non-Commuter	SOV, HOV-2, HOV-3+	cost c2
19	16	Long Distance	All	Regional	Commercial	cost e2
20	17		All	Regional	Medium Truck	cost e2
21	18		All	Regional	Heavy Truck	cost e2
22	19		All	Regional	Regional autos	cost e2
23	20		All	Regional	Regional trucks	cost e2

Note: *: Considered as a home based trip with income category 3; **: Considered as a non-home based trip with income category 3

CASE STUDY

The case study applies the model methodologies developed earlier in our paper to analyze commuter behavior for multiple sub-regions in the Capital mega-region. Figure 1 shows the geography of the study area, which is subdivided into 1,607 Mega-region Modeling (Traffic) zones (MMZ). The complete model also includes a zone super structure of 131 National Modeling Zones (NMZ) which covers the rest of the United States. The regional zones are included in the model to incorporate long distance and regional travel originating or destine for zones outside of the mega-regional study area. The model is constructed with a generalized highway network with several levels of facility types including all interstates, major highways and many arterials. The network consists of over 167,000 links with 20 facility types including both highway and transit.

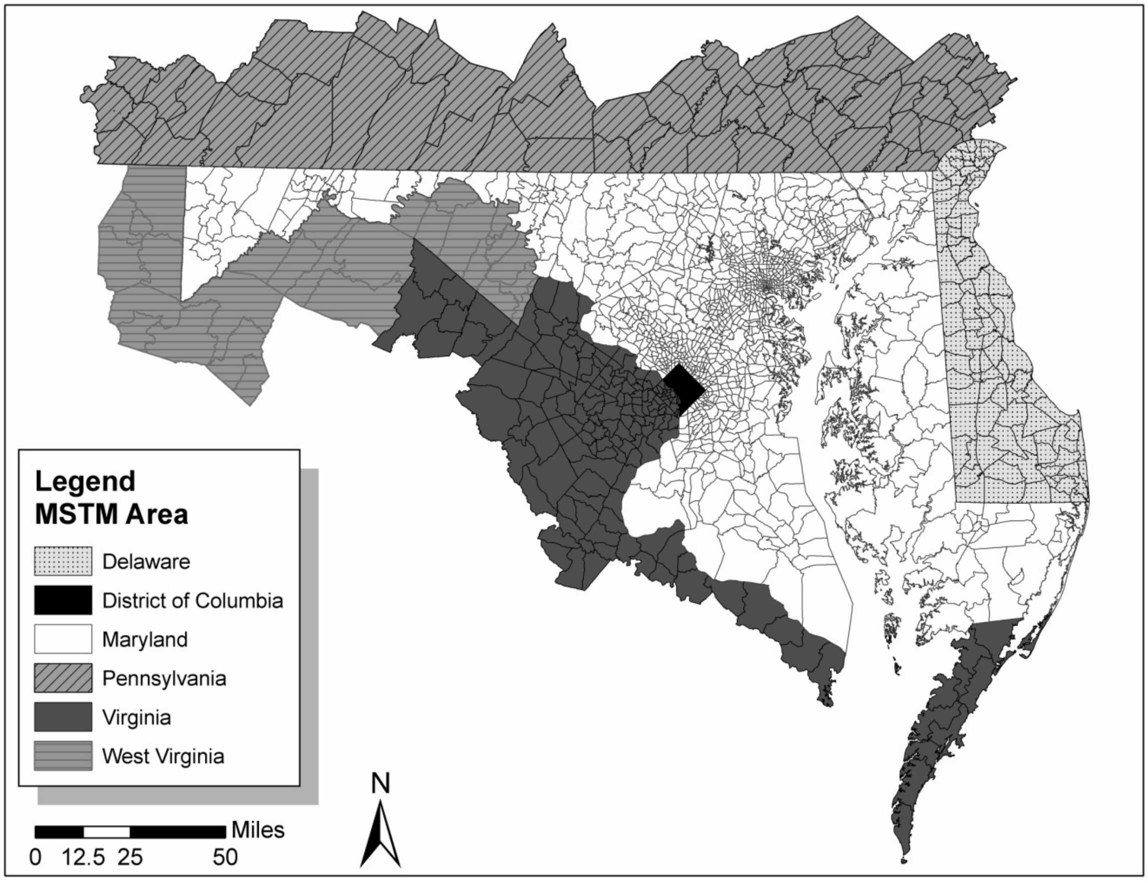
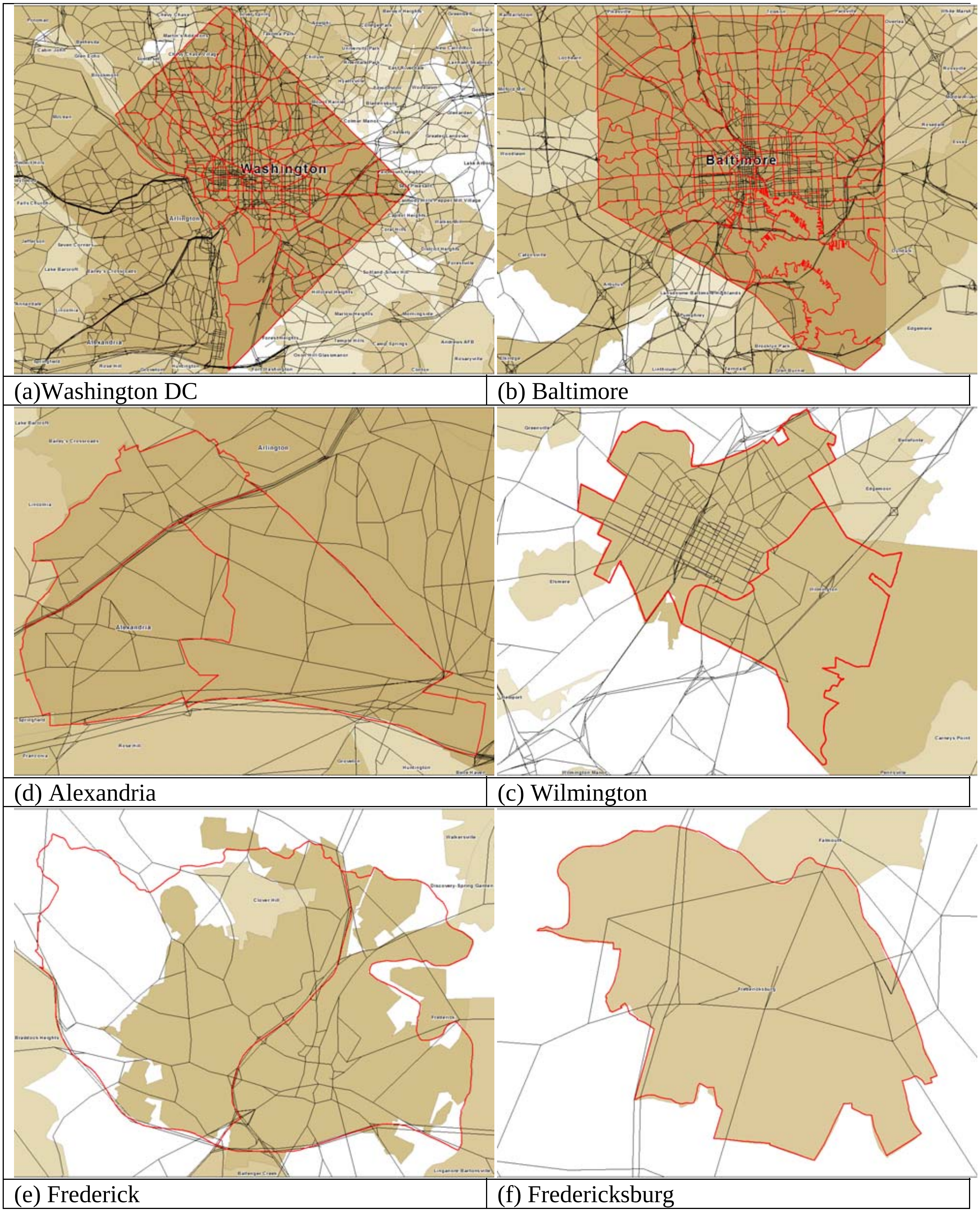


Figure 1 Mega-region (Traffic) Modeling Zones

To demonstrate how highway users behave in response to priced links in locations with unique characteristics, we further divided the Capital mega-region into six metropolitan areas. These six metropolitan areas vary in terms of population, density, geographic scope, average income and highway network complexity. The network and zone system of the six metropolitan areas selected for analysis is shown in Figure 2. The locations are arranged (from “a” to “f”) in order of descending size, density, and complexity. The first two (“a” and “b”) metropolitan areas are the largest mega-region, Washington DC and Baltimore (city). The next largest area is Alexandria which is situated just south of Washington DC. Wilmington (“d”) is located in the northeast corner of Delaware. Frederick (“e”) is the second largest city in Maryland, after Baltimore. Finally, Fredericksburg is rural but rapidly growing independent city about 50 miles south of Washington in Virginia.



(a)Washington DC | (b) Baltimore | (d) Alexandria | (c) Wilmington | (e) Frederick | (f) Fredericksburg

Figure 2 Zone System and Networks of Six Major Metropolitan Areas in Mega-Region

The case study follows that same methodology developed in earlier parts of this paper and in the example problem. A Base-case is specified which represents current highway network travel activity and three models with tolling and differing levels of VOT are developed. A toll of $0.50 per mile is applied to interstate facilities that intersect the border of each of the six mega-regional metropolitan areas. In the cases of Washington DC and Baltimore the toll is also applied to interstate beltways that surround the city border but to not enter into the city. The toll is equivalent to a congestion charge as the pricing mechanism is implemented only during the peak AM and peak PM periods.

RESULTS AND DISCUSSION

We constructed a Base-case and three models to illustrate user response to road charges with a typical multiclass assignment model specification where users' value-of-time is based only on their income categories and then with trip purpose differentiated VOT. For the purpose of this case study, there are two types of trips differentiated. The first trip purpose is for commuting and the other is for non-commute trips. The distinction in VOT between these trips is that VOT for commuting trips in each income category is twice (similar to the example problem) the VOT for non-commuting trips.

Assignment Results and Elasticity

The Base-case scenario is used as a reference point to measure how users respond to road charges in each of the three models. The results for the Base-case and three models are presented from the PM peak period. For brevity, AM, Mid-day, and Nighttime period results are not presented. However, it should be noted that the model produces outputs for all time periods. Table 4 shows the number of commute trips without a VMT based toll and with VOT by income class only. In the six selected cities there are a total of about 3.2 million vehicle trips on specific interstates that will be subjected to congestion charging in the models. On these facilities in the Base-case nearly 50% of all travel is composed of commute trips. The composition of income in each of these trip purposes is significantly different; for commuter trip purposes the majority of trips are in the lower income groups while the majority of trips in the non-commute purpose are in the higher income categories. For example, among all regions analyzed, Income group-3 has the highest number of commuters (916,647) where income group-4 and group-5 carry the lowest number of commuter trips. In contrast, for non-commuter trips, income group-4 has the highest number of trips (1,133,449) and income group-1 has the lowest number of non-commuter trips.

TABLE 4 Base-case Highway Vehicle Trip Volumes

Location	Base-case									
	Commute Trips					Non-commute Trips				
	INC 1	INC 2	INC 3	INC 4	INC 5	INC 1	INC 2	INC 3	INC 4	INC 5
Washington DC	45,049	143,272	326,008	7,281	23,726	6,293	12,595	22,307	806,619	133,999
Baltimore	89,815	250,366	488,380	7,397	27,327	16,934	26,075	36,783	910,128	141,212
Wilmington	5,324	12,929	22,712	759	2,730	1,649	2,365	4,021	58,031	5,992
Fredericksburg	374	950	2,173	393	581	239	360	830	6,574	985
Alexandria	7,080	24,652	54,577	2,313	5,250	1,280	2,617	4,562	105,471	22,795
Frederick	4,223	11,588	22,797	1,060	5,118	1,978	3,426	6,571	53,245	8,844
TOTAL	***151,865***	***443,757***	***916,647***	***19,203***	***64,733***	***28,373***	***47,437***	***75,075***	***1,133,449***	***313,826***

Model-1 institutes the $0.50 per mile congestion charge on major interstate corridors within or near each if the six metropolitan areas. Table 5 presents the elasticity of demand from the pricing. The results indicate how pricing affects route taking decisions especially where VOT is low (income groups 1-3). The results show that users in the lowest income categories are the only group that is elastic to changes in pricing. In other words, higher income group travelers continue to use the same path even when the link is priced. Other income groups have a VOT high enough that the pricing of a road segment along a selected path does not significantly affect the path selection process.

The results of our model have some implications on a mega-regional scale. Areas of higher density tend have a higher elasticity of demand in terms of toll, with some exceptions. In Model-1 where all road users are not differentiated by trip purpose, the elasticity of all six areas combined ranges from .99 for the lowest income group to .28 for the highest income group for commute trips. For non-commute trips, elasticity for the lowest to highest income group ranges from .99 to .30 respectively. The smaller cities of Fredericksburg and Wilmington display unitary elasticity for lower income travelers both commuting and non-commuting. This indicates that users are more responsive to changes in road cost in these areas compared more dense locations. The larger cities of Frederick and Washington DC are relatively inelastic to toll charges even for lower income groups. This is likely because the demand for travel in these areas is such that it is more efficient to pay a toll than select another route. The cities of Baltimore and Alexandria present a different scenario. In these areas there was already a road charge on at least one road section prior to the new VMT based toll. When the new toll is instituted, users are elastic to further increases in travel costs. The reason for this higher elasticity is that tolls are already in place on high demand facilities were there are few alternative routes; instituting an additional toll on these facilities increases cost, but because initial demand is so high the toll cost plus travel time makes many lower income users seek alternatives while higher income users take advantage of lower travel time.

Model-2 uses the same congestion charging system as in Model-1, but in this case both income groups and trip purposes (commuter and non-commuter) have different values-of-time. When commuters are faced with a toll, they tend to accept the toll rather than seek substitutes. The combined elasticity for all six cites went from a range of .99 to .29 in Model-1 from each income group a range of .95 to .17. Non-commuters in most cases were slightly more elastic to pricing. In locations where a there was an additional pre-existing toll, road users remained elastic to the pricing. This suggests that even when users have very high VOT, they are still sensitive to very expensive road prices. Road conditions are a complex phenomenon and some of this complexity is picked up in in the Model-2 elasticity results. Commuters in the higher income class appear to become more sensitive to tolls when the commuter trip purpose VOT increases. This occurs because as lower income commuters become less elastic to pricing, road conditions become worse. As traffic flow decreases higher income commuters seek out faster and cheaper alternatives at a greater rate. This has an important implication for equity concerns over congestion charging. While higher income groups to have a lower elasticity to pricing, when all commuters face the same toll, the disparity of travel costs between income groups shrinks, reducing the differential impact of tolls on each income group.

Model-3 is formulated in the same way that model-2 is constructed but models variable demand rather than static demand. In the previous models, users were sensitive to trip cost only in selecting a route. In Model-3 users are sensitive to price not only when selecting a route, but also when deciding whether or not to take a trip and by which mode. The results show the somewhat paradoxical effect of user decision making under variable demand conditions (cells shaded in gray). For higher income commuters the elasticity of demand for tolled roads appear to mimic a Giffen good, that is, when the toll cost of the facility increases, the demand for travel on the facility for higher income groups, increases. This is an example of the complexity of the highway network. Users in lower income groups and especially non-commuters are much more elastic to tolling. Under variable demand when the price to travel on the road increases, users simply decide not to travel or seek alternative modes. This in turn reduces the travel time on the tolled roads making the road more attractive to commuters.

TABLE 5 Elasticity of Demand for $0.50/mile toll

Model	Location	Elasticity of Demand with Respect to Tolls									
		Commute Trips					Non-commute Trips				
		INC 1	INC 2	INC 3	INC 4	INC 5	INC 1	INC 2	INC 3	INC 4	INC 5
Model-1	Washington DC	-0.91	-0.67	-0.34	-0.20	-0.22	-0.92	-0.63	-0.31	-0.34	-0.25
	Baltimore	-1.02	-0.86	-0.54	-0.40	-0.36	-1.01	-0.84	-0.48	-0.51	-0.38
	Wilmington	-1.00	-0.74	-0.20	-0.25	-0.19	-1.00	-0.75	-0.27	-0.23	-0.17
	Fredericksburg	-1.00	-0.41	-0.12	-0.08	-0.09	-1.00	-0.36	-0.17	-0.13	-0.10
	Alexandria	-1.28	-0.44	-0.20	-0.27	-0.25	-1.30	-0.70	-0.36	-0.30	-0.18
	Frederick	-0.87	-0.55	-0.27	-0.35	-0.29	-0.90	-0.64	-0.39	-0.34	-0.22
	TOTAL	-0.99	-0.75	-0.42	-0.29	-0.28	-0.99	-0.75	-0.40	-0.15	-0.30
Model-2	Washington DC	-0.81	-0.28	-0.11	-0.23	-0.25	-0.92	-0.65	-0.34	-0.37	-0.28
	Baltimore	-1.02	-0.43	-0.23	-0.43	-0.39	-1.01	-0.85	-0.50	-0.53	-0.40
	Wilmington	-0.96	-0.16	-0.06	-0.30	-0.20	-1.00	-0.76	-0.31	-0.27	-0.19
	Fredericksburg	-0.64	-0.10	-0.04	-0.09	-0.13	-1.00	-0.34	-0.17	-0.13	-0.11
	Alexandria	-1.31	-0.22	-0.07	-0.42	-0.40	-1.35	-0.74	-0.40	-0.33	-0.21
	Frederick	-0.69	-0.23	-0.08	-0.35	-0.29	-0.90	-0.66	-0.39	-0.34	-0.22
	TOTAL	-0.95	-0.35	-0.17	-0.32	-0.31	-0.99	-0.76	-0.42	-0.18	-0.32
Model-3	Washington DC	-0.88	-0.50	-0.38	0.92	0.84	-0.94	-0.75	-0.54	-0.98	-0.79
	Baltimore	-1.05	-0.66	-0.51	0.98	0.79	-1.02	-0.92	-0.71	-1.02	-0.89
	Wilmington	-0.98	-0.34	-0.27	0.87	0.59	-1.00	-0.84	-0.46	-0.96	-0.68
	Fredericksburg	-0.75	-0.25	-0.26	0.51	0.28	-1.00	-0.35	-0.25	-0.90	-0.65
	Alexandria	-1.59	-0.69	-0.56	1.73	1.53	-1.40	-0.96	-0.74	-1.38	-1.09
	Frederick	-0.85	-0.51	-0.37	0.80	0.25	-0.96	-0.83	-0.66	-0.95	-0.71
	TOTAL	-1.01	-0.59	-0.45	0.98	0.84	-1.01	-0.86	-0.63	-1.00	-0.84

Cross Price Elasticity

Table 6 provides that cross-elasticity of demand for non-tolled alternatives. These elasticities represent the demand for non-interstate facilities in each of the six cities when a toll is initiated on the interstates. As expected, since the elasticity of demand in most areas is below one, the substitution of interstate routes is low as well. In Wilmington, one of the two most remote cities, the substitution effect is high for the lower income group but is roughly the average for all other income groups. This indicates that many of the other routes within Wilmington that offer a substitute are substantially time consuming. In most other cases, there is a lack of quality substitutes for interstate travel. As a result, planners in a mega-regional context will likely not have to worry about local roads congesting if a moderate VMT based toll is instituted on interstates.

The cross elasticities for Model-2 behave as expected. In Wilmington commuters still seek out local road to avoid toll charges as is the case with Alexandria where there is a pre-existing toll. Non-commuters do not appear to seek out alternatives, rather they avoid the area altogether. The Giffen effect is preserved in Model-3 even for non-tolled alternatives. Some users find the time-cost of travel on non-interstates too high and select not to make a trip. This in-turn makes travel on these routes relatively more attractive so higher income users travel on these roads.

TABLE 6 Cross-elasticity of Demand

Time of Day	Location	Cross-Price Elasticity									
		Commute Trips					Non-commute Trips				
		INC 1	INC 2	INC 3	INC 4	INC 5	INC 1	INC 2	INC 3	INC 4	INC 5
Model-1	Washington DC	0.05	0.04	0.04	0.01	0.01	0.01	0.01	0.01	0.02	0.03
	Baltimore	0.13	0.14	0.13	0.02	0.04	0.04	0.05	0.04	0.08	0.09
	Wilmington	0.33	0.28	0.07	0.04	0.03	0.14	0.12	0.04	0.04	0.03
	Fredericksburg	0.02	0.03	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.00
	Alexandria	0.28	0.22	0.15	0.05	0.05	0.10	0.09	0.06	0.10	0.07
	Frederick	0.15	0.10	0.06	0.04	0.03	0.06	0.05	0.04	0.05	0.04
	TOTAL	0.11	0.10	0.08	0.02	0.02	0.03	0.04	0.03	0.05	0.05
Model-2	Washington DC	0.04	0.03	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.03
	Baltimore	0.12	0.09	0.08	0.02	0.05	0.04	0.05	0.04	0.08	0.09
	Wilmington	0.32	0.05	0.00	0.06	0.03	0.14	0.12	0.06	0.06	0.03
	Fredericksburg	0.03	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.00
	Alexandria	0.45	0.13	0.07	0.09	0.07	0.09	0.09	0.06	0.11	0.08
	Frederick	0.12	0.05	0.02	0.03	0.04	0.06	0.06	0.04	0.05	0.05
	TOTAL	0.11	0.06	0.05	0.02	0.03	0.04	0.04	0.03	0.05	0.06
Model-3	Washington DC	-0.24	-0.22	-0.25	0.73	0.51	-0.24	-0.23	-0.25	-0.95	-0.62
	Baltimore	-0.18	-0.16	-0.19	0.76	0.42	-0.22	-0.20	-0.21	-0.99	-0.79
	Wilmington	0.05	-0.29	-0.36	0.39	-0.12	-0.11	-0.12	-0.24	-0.94	-0.53
	Fredericksburg	-0.23	-0.22	-0.24	0.51	-0.12	-0.24	-0.22	-0.23	-0.83	-0.46
	Alexandria	-0.07	-0.30	-0.45	1.17	0.22	-0.26	-0.25	-0.29	-1.29	-0.89
	Frederick	-0.17	-0.20	-0.24	0.67	-0.08	-0.20	-0.20	-0.22	-0.87	-0.48
	TOTAL	-0.20	-0.20	-0.24	0.76	0.45	-0.22	-0.21	-0.23	-0.99	-0.69

Tolls and Road Conditions

While tolling has a differential impact on each income group and trip purpose, there is a net impact on the road network when modeling response to tolls, shown in Table 7. Model-1 shows a 30% reduction in VMT, a 36% reduction in VHT and a 70% reduction in congested lane miles (CLM). Model-2 shows a smaller effect with a 24% reduction in VMT, a 29% reduction on VHT and a 62% reduction on CLM. Finally, Model-3 has the largest impact on network conditions. When interstates in the six cities are tolled and user response is modeled with variable demand, there is a 39% reduction on VMT, a 46% reduction in VHT and an 86% reduction in CLM.

TABLE 7 Network effects

Location	**Base-case**			**Model-1**			**Model-2**			**Model-3**		
	VMT	VHT	CLM	VMT	VHT	CLM	VMT	VHT	CLM	VMT	VHT	CLM
Washington DC	2,042,528	54,405	189	-25%	-34%	-58%	-19%	-27%	-49%	-35%	-47%	-81%
Baltimore	1,797,002	39,952	100	-40%	-43%	-100%	-32%	-35%	-96%	-47%	-50%	-100%
Wilmington	169,501	3,548	0	-20%	-20%	N/A	-17%	-18%	N/A	-29%	-29%	N/A
Fredericksburg	95,532	2,164	11	-7%	-15%	0%	-5%	-12%	0%	-7%	-18%	0%
Alexandria	265,089	6,296	27	-25%	-29%	-68%	-19%	-23%	-58%	-38%	-44%	-100%
Frederick	145,520	2,872	5	-25%	-28%	-71%	-21%	-23%	-71%	-36%	-40%	-88%
TOTAL	***4,515,173***	***109,236***	***333***	-30%	-36%	-70%	-24%	-29%	-62%	-39%	-46%	-86%

SYNTHESIS OF RESULTS

The results of the Base-case and three models show that users are not as elastic to price as one would assume, however users in different income groups and travelling for different purposes widely vary in response. This is partly due to the lack of available substitutes for interstates and partially due to the composition of income within trip purposes. Non-commuters have a generally lower value of time especially when VOT for commute trips is doubled, but the effect in elasticity of demand appears somewhat muted by a substantially higher level of upper income trips taken for non-commuting purposes. This is just one of the complexities of user response to highway network congestion charging. Understanding user elasticity to tolling is also important for policy-makers and planners to determine how non-tolled facilities will be impacted by tolls and the potential for revenue generation. The results indicate that areas of higher density tend to have a higher elasticity of demand in terms of tolls. In terms of cross-price elasticity between tolled interstates and non-tolled alternatives, there seems to be very little substitution. Modeling the unique effects of tolls in different sized cities in the context of a mega-region provides new insight on how road users in different metropolitan areas are likely to respond to tolls and how a large mega-regional network is impacted by toll policy

The results of the models show that in non-purpose differentiated VOT models, users in the lowest income categories are the only group that are elastic to changes in road pricing. Lower income travelers are elastic to new tolls on existing tolled facilities, while higher income travelers take advantage of the absence of lower income travelers on these facilities. The representation of road users with different trip purposes and corresponding VOT, measures how each group of road user will respond to changes in road cost. This segmentation of users has important implications for policy.

When purpose differentiated congestion charging is applied to a mega-region, commuters in the higher income classes appear to become more sensitive to charges when the commuter trip purpose VOT increases. This occurs because as lower income commuters become less elastic to pricing and road conditions become worse. When all commuters face the same charge, the disparity of travel costs between income groups shrinks, reducing the differential impact of tolls on each income group. When a variable demand model is implemented to capture user trip decision making, a somewhat paradoxical effect occurs for commute travelers. For higher income commuters the elasticity of demand for tolled roads appears to mimic a Giffen good, that is, when the toll cost of the facility increases the demand for travel on the facility for higher income groups, increases. This provides an example of the complexity involved with toll policy and network effects, which only grows more complex in a mega-regional context.

CONCLUSION

Congestion pricing for the purpose of travel demand management has become a hot topic of debate among transportation planning agencies. In the US, a number of metropolitan areas have studied their potential implications, and some have implemented these policies on a limited number of links. Internationally, a few places such as, Stockholm and London, have implemented area-wide congestion pricing, and preliminary evaluation of their outcomes have presented valuable lessons in assessing user behavior. At the mega-regional level however, added computational and institutional challenges add to the complexity of assessing and implementing congestion pricing. In advancing the use of VOT, we tackle a key such challenge in this paper.

In this paper, two contributions are made. First, a methodology is presented to examine commuter/non-commuter travel behavior using VOT cross-classified by income and trip purpose. Second, the methodology is applied to the Capital mega-region, and travel behavior is studied for its six sub-regions. We used a trip based four-step travel demand model for the analysis with a Base-case and different three models. Mid-point arc elasticity was used to compare the model performances to that of the Base-case. Cross price elasticity was used to compare the performance between the toll and non-toll cases. Finally aggregate measures such as VMT, VHT, and CLM were used to compare all four scenarios.

The proposed tools can be very useful for engineers, planners, and policy makers to examine travel behavior when congestion pricing is considered and travel behavior is analyzed using VOT by income and trip purpose. In the future scope of work, we will derive the VOT by income and trip purpose from a specially designed survey and then analyze the travel behavior in a mega-regional context. We also plan to use the travel model to answer other questions such as first/second best toll, highway capacity expansion, freight alone corridor, and highway financing.

Overall, our analysis adds to the argument that simply expanding regional boundaries to meet the extents of ever-changing economic systems and applying traditional methods at new scales will not be adequate to resolve key issues in the long run. Institutionally, new frameworks are needed in which federal dollars can accurately target projects that cross existing planning spheres (be it MPO, State, or other) and intergovernmental decision-making is encouraged. At the same time, improved analytical approaches are needed to better realize the potential for mega-regional planning decisions.

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