TRAFFIC AND WELFARE IMPACTS OF CREDIT-BASED CONGESTION PRICING APPLICATIONS: AN AUSTIN CASE STUDY

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Transportation Research Record 275(1): 10-24 (2020).

ABSTRACT

To dramatically reduce traffic congestion, improve road operations, and benefit many travelers, this paper applies policies of credit-based congestion pricing (CBCP) across the Austin, Texas regional network. Scenarios evaluated include those selecting links with maximum delays, by variably tolling bridges and by recognizing congestion externalities across all links. Travel demand models with full congestion feedback are used to deliver inputs for normalized logsum differences to quantify and compare consumer surplus changes across traveler types, around the region. This study aims to find a harmonic condition between decreasing traffic congestion and improving travelers' welfare by changing tolling values and tolling links simultaneously. Results suggest that limited tolling locations under four broad times of day can do more harm than good, unless travelers shift out of the PM and AM peak periods. When using CBCP across all congested links at congested times (10% of revenues will be used as administrative costs) of day, an average benefit of $1.61 per licensed driver per weekday is estimated, with almost all travelers benefiting, and 95.04% traffic analysis zone's (TAZ) value of travel time (VOTT) group 1 (VOTT is $5/h) will benefit from the CBCP. Using twice the difference between marginal social cost (MSC) and the average cost (AC) (on each subset of links) appears to benefit more people, although tolling high on various links adds to congestion elsewhere. Tolling on top 500 links will benefit 97% of TAZs' VOTT3 (VOTT is $25/h) travelers & 99% of TAZs' VOTT5 (VOTT is $45/h) travelers.
Keywords: Travel Demand Modeling, Credit-based Congestion Pricing, Traveler Welfare, Traffic Congestion, Travel Behavior.

BACKGROUND

Researchers have recognized the negative externalities brought by traffic congestion and showed that congestion pricing (CP) is a way to internalize the congestion external cost and alleviate traffic congestion (Vickery, 1969; Vehoef et al., 2000; Yang, 2000) through influences on users' travel behavior and thus effects on travel cost and time (Vehoef et al., 2002; Paleti et al., 2014; Lu et al., 2015; Liu et al., 2017; Romero et al., 2019; Huan et al., 2019). CP increases the direct travel cost for some routes and preserves competitive access to some congested links, which results in the redistribution of traffic across time and space throughout the network. Travelers perceiving different value of travel times (VOTTs) present different travel behavior in response to CP, reflected by destination choice, departure time choice, route choice and mode choice. Under the CP policy, travelers may choose a closer destination, alter mode of transit, shift departure time to off-peak time, and detour to avoid congested links or peak time (Yamamoto et al., 2000), which will decrease traffic volumes on the congested links and reduce congestion across the network (Li, 1999; Yang & Huang, 1999; Cheng et al., 2017; Hall, 2018). According to BPR function (BPR, 1964), less traffic volume on the link leads to reduced travel time, along with lower levels of driving stress during congestion (Stefanello, et al., 2017), decreased fuel cost, decreased vehicle-hours traveled (VHT) and vehicle-miles traveled (VMT), and increased consumer surplus (Gupta et al., 2006).

After first being introduced in Singapore in 1975, CP was implemented and analyzed in many cities, including London (Schade & Baum, 2007), Stockholm (Eliasson & Jonsson, 2011), Gothenburg (Börjesson et al., 2015), Bergen and Oslo in Norway (Tretvik, 2003), and New York City in the United States (Schaller, 2010). CP has shown merit during its implementation, but many disadvantages have been revealed. Although Van den Berg & Verhoef (2011) indicated that CP can improve social welfare of the majority (55% in first-best pricing) of travelers (even without returning toll revenues to them), CP implementation effects depend largely on drivers' acceptability and responses (Gibson et al., 2015) because of the equity and fairness issues (Eliasson et al., 2016). This policy is often rejected by the public because it is considered an additional tax (Cipriani et al., 2019), or a cost that was free previously. Critics often suggest that CP is unfair for traveler groups with lower income (Ecola & Light, 2009), because it ignores people's affordability and burdens low-income drivers. With CP, road users with a high VOTT are more willing to pay to experience less travel delay, while low VOTT roadway users are more likely to give the right of way to high VOTT travelers by shifting travel mode, departure time and routes to avoid paying tolls. Arnott et al. (1988) and Lindsey (2004) pointed out that user heterogeneity in VOTT and trip-timing preferences cannot be ignored, influencing on traffic assignment and welfare effects (Van den Berg, 2014).

Credit-based Congestion Pricing Policy (CBCP)

In order to reduce negative impacts of CP and boost the acceptance of CP policy, most roadway users should benefit from traffic demand management policy (Adler et al., 2001). Credit-based congestion pricing (CBCP) policy is proposed by Kockelman and Kalmanje (2004) as a revenue-neutral strategy to tackle the equity issue, by allocating the toll budget as credits given back to eligible travelers. Under CBCP, drivers who shift their departure time or routes may pay nothing or even make money, while those who still travel at peak hours or travel long distances will pay money. As a major difference from CP, travelers with small VOTTs who make sacrifices to reduce network congestion (e.g. give up driving cars, departing at non-peak times or detouring to uncongested routes) can receive credit as compensation. Kockelman and Kalmanje (2004) concluded that CBCP may provide the most equitable and efficient implementation alternative, have the potential to alleviate traffic congestion, and benefit most travelers across the region. They suggested that most Austin residents would be better off under policies that employ CBCP (tolling all roads), whereas relatively few would benefit under a simple CP policy. Kockelman and Kalmanje (2005) polled the public in Austin, TX, and CBCP turned out to be a competitive option. Gulipalli (2011) also interviewed and received feedback from transportation economists, toll technology experts, highway administrators, and policy makers in 2011, and concluded that CBCP may be viable both politically and technologically, regarding the rapid technology advancement and increasing congestion in many urban regions. Gulipalli and Kockelman (2008) evaluated distinctive CBCP policies across the Dallas-Fort Worth, Texas metroplex by estimating traffic, air-quality and welfare impacts of pricing all congested links versus along major highways, relative to the status quo scenario. They estimated that 50-65% of travelers in the Dallas-Fort Worth 9-county region would benefit from the tested CBCP policies, while removing all heavy-congested roadway points (except unexpected events, like crashes removing a freeway lane from use) in an efficient and equitable way. Kockelman and Lemp (2011) used logsum differences to anticipate mode, destination, route-choice, travel time, traffic, and consumer welfare effects of CBCP for a toy network across three times of day (AM, mid-day [MD] and PM). Recognizing two groups of travelers (high VOTT versus low VOTT), they estimated how travelers (especially travelers with low VOTT) would be better off if one of the two routes to the distant destination was operated under a CBCP policy.

First-best and Second-best Tolling Strategies

Due to variable-toll information issues and relatively high toll-application costs of the past, researchers and policymakers have focused on “second-best” deployments, like tolls on a small subset of links or use of area-type or cordon-type tolls (Verhoef, 2002; Yang et al, 2003; Rouwendal and Verhoef, 2006; Verhoef et al., 2010). First-best congestion pricing requires pricing of congestion externalities in real time on all congested links, making it impractical in the past or many current settings (Kockelman et al., 2011; Gholami, et al., 2015; Cheng et al., 2019, Cipriani et al., 2019). Noted by Zhang and Ge (2000 & 2004), first-best toll applications can significantly increase information and uncertainty burdens on roadway users, resulting in political resistance to their implementation. Many thoughtful versions of second-best pricing can harmonize system efficiency gains, system investment and operating costs (Johansson & Sterner, 1998). Gupta et al. (2006) found that it may be wise to price only Austin’s bridges during peak times of day to achieve consumer surplus gain and dramatically relieve the region’s congestion, rather than applying MCP (Marginal Cost Pricing) at all congested times of day on all bridges.

Most CBCP research to date (Gulipalli & Kockelman, 2008; Kalmanje & Kockelman, 2009; Lemp & Kockelman, 2009) puts emphasis on freeway tolls, due to the real cost of toll collection using past technologies. Most CP research focuses on small and generic networks (Verhoef et al., 2002 & 2010; Yang et al., 2003; Zhang et al., 2004; Koh et al., 2009), with difficulty in calculating and optimizing across complex, real networks. Recognizing the potential benefits of CBCP policy and emerging technologies (for 5G cellular applications, with free real-time routing guidance and low-cost on-board dongles, for example), this paper applies various road-pricing strategies across Austin’s 6-county region to compare the effects of different tolling strategies on travelers’ behavior, traffic and welfare. Using the Capital Area Metropolitan Planning Organization’s (CAMPO’s) year-2020 networks and household travel demand assumptions, this work identifies the most “congested” (i.e., delay-inducing, due to high travel and high delays) 100 links among Austin’s 25,176 coded roadway links, calculates the difference between the MSC (Marginal Social Cost) and AC (Average Cost) as the toll value, and then draws them on the map and finds the distribution of the most congested links. To see if limited tolling applications may be helpful, the work simulates scenarios of tolling the worst 25 links, then the worst 50, 100, 500, and 1000 links in this network, and analyzes their delay impacts respectively. Since these scenarios will mostly add VMT and VHT (as motorists largely shift to more circuitous routes), the work compares the effects of tolling the region’s 7 bridges across the Colorado River, to avoid re-routing options for those with origins and destinations on opposite sides of these famously congested links. Finally, it recognizes the option of GPS-based tolling to apply CBCP across all congested links, across the four broad times of day that align with CAMPO's trip-based model. In all scenarios, two modes of travelers (automobile and bus) are sorted by 5 VOTT classes (from $5/hr to $45/hr, in steps of $10/hr), and 3 trip purposes (home-based work [HBW], home-based non work [HBNW] and non-home based [NHB]) in four times of day (AM, PM, MD, NT [night]). Traffic and welfare impacts of these strategies are compared and analyzed based on simulation results. More details on methods and results are provided in the following sections.

METHODOLOGY

This section introduces the methodologies used to simulate and analyze the influence of CBCP policy, including travel demand model descriptions as well as the methods that are used to calculate toll values, pick out the top worst links and compute welfare changes. The methodology provided in this section can be used to seek a balance between decreasing traffic congestion and improving traveler welfare by changing the number of tolling links and tolling values of links. The number of tolling links (the worst 25, 50, 100, 500, and 1000 links, and 7 bridges) and three types of tolling values are combined as testing scenarios to be simulated in the travel demand model.

Travel Demand Model

The Travel demand model used in this paper is a traditional four-step model, including trip generation, trip distribution, mode choice, time of day and traffic assignment. As noted in previous sections, travelers were divided into five VOTT groups from $5/hr to $45/hr ($5/hr, $15/hr, $25/hr, $35/hr and $45/hr) to evaluate the influence of CBCP on travel patterns and road conditions. Each VOTT group represents one household income group that is categorized by the CAMPO travel demand model (2010), which also provides the share of each group in each traffic analysis zone (TAZ). These five income groups are households with income under $19,999, between $20,000 and $34,999, between $35,000 and $49,999, between $50,000 and $74,999 and over $75,000, respectively. The median income of the five income groups can be transferred to VOTT as $4.96/hr, $13.64/hr, $21.08/hr, $31/hr and over $37/hr respectively (Median income per year divided by a factor of 2016 (21 workdays in a month × 12 months in a year × 8 work hours in a day). Therefore, VOTTs for the five groups were assumed to be from $5/hr to $45/hr, in steps of $10/hr, for easy scenario comparisons.

Trips made by these five VOTT groups in each TAZ were also categorized by three trip purposes. In terms of HBW and HBNW trips in every TAZ, trip production by a VOTT group was determined by the TAZ's total production of the specific purpose, multiplied by the population percentage of the corresponding income groups. NHB trips produced by five VOTT groups were assumed to be evenly distributed across the population, because NHB is more complex and not directly correlated with family income. Using the Quick Response Method trip generation module in TransCAD 7.0, trip productions in each TAZ are calculated based on income per household (median income), household auto ownership (e.g. 0, 1, 2, or 3+) and retail and non-retail employment in each TAZ. TransCAD includes a trip-rate cross-classification table from NCHRP 187 that can be used to estimate trip rates based on a TAZ's average demographics which were obtained from the CAMPO model directly (e.g. number of person trips produced per TAZ by each household income group and household auto ownership in this paper). This trip production rate was multiplied by the number of corresponding traveler groups to obtain the total production of that group. The attraction model is a regression equation that estimates the number of person trips attracted to a zone, based on retail and non-retail levels of employment in the zone in 2020. The trip generation table was balanced by holding production constant and adjusting attractions. The trip generation step obtained 15 tables of production and attraction for the five VOTT groups by three trip purposes.

After that, trip distribution was implemented separately for each VOTT group by purpose. The impedance function (Gamma function) used shortest path travel time as the impedance which considers the influence of the toll value. A binary logit mode choice model was then conducted considering only two modes (automobile and bus) for the five VOTT groups using different VOTTs, which are reflected in the utility function. Automobile utility was calculated based on cost and in-vehicle travel time (IVTT) of the five user groups, and the utility of buses was calculated by fare and IVTT. Automobile cost contains operating cost and parking cost at the destination. Model specifications for mode choices were adapted from Zhao and Kockelman (2018). Parameters of automobiles were distinct for the five VOTT groups (IVTT: -0.019; cost: -0.228, -0.076, -0.0456, -0.033 and -0.025 for five VOTTs). VOTT of all bus users was assumed to be homogenous as $8.14/hr (IVTT: -0.019; cost: -0.14) (Zhao &Kockelman, 2018), because buses are more likely to be favored by low VOTT groups. Kouwenhoven et al., (2014) estimated that VOTTs of bus riders in the Netherlands varies between €7.75/hour and €10.50/hour ($8.5/hr - $11.5/hr). Winter et al. (2019) proposed that for the regular bus, mean VOTT is €5.13/hr ($5.6/hr). Therefore, a VOTT of $8.14/hr can be considered a reasonable assumption.

Fifteen production-attraction tables (for the five VOTT groups and three trip purposes separately) were obtained from mode choice, while the time of day procedure transformed them into 15 origin-destination tables. Time of day was divided into four time periods: 3 hours (6 am to 9 am) for AM peak, 6 hours (9 am to 3 pm) for MD, 4 hours for PM peak (3 pm to 7 pm), and 11 hours for NT (from 7 pm to 6 am). The PA-OD procedure and time of day transformations (requires an Hourly Lookup Table provided by CAMPO and adjusted by the road network traffic characteristics) are processed at the same time. The time of day procedure takes a 24-hour matrix, with information on the percent flow per hour, and produces hourly matrices. This procedure also provided means to convert person trips to vehicle trips. This conversion is based on hourly vehicle occupancy factors, specific to each hour in the day (1.5 for cars and 1 for truck (CAMPO, 2010)). A multi-modal multi-class traffic assignment (MMA) was carried out for the region's two modes: automobiles (5 VOTT groups and 3 trip purposes) and commercial trucks. MMA allows researchers to explicitly model the influence of toll, each mode or class can have different congestion impacts (passenger car equivalent values), values of time, and toll cost. The commercial truck trip table was obtained from the CAMPO model directly. The convergence criteria are assessed by a relative gap that is an estimate of the distance between the sum of current travel time on links and sum of travel time on links in the last iteration. The convergence threshold is 0.0001 and the number of iterations is 500 in each feedback iteration.

Bureau of Public Roads (BPR) link performance function was used to calculate travel time (BPR, 1964).

$$t_l = t_{FFT,l}(1+\alpha(v_l/c_l)_\beta) \qquad (1)$$

where t_l is the travel time on link l, $t_{FFT,l}$ is the free flow travel time on link l, v is the traffic flow on link l, c is the capacity of link l, v/c is the traffic service level, alpha and beta parameters are obtained from the CAMPO model. Travel time in each MMA will be fed back to the second step of traffic demand model (trip distribution) in the next iteration until they remain stable or meet the convergence criteria. Method of successive average is used to update travel time in each iteration. Due to computation complexity, 10 feedback iterations are used.

Tolling Strategy

Tolling strategies include the method of selecting toll links as well as toll value calculation. Toll links are selected based on the traffic assignment results from the base case scenario. Specifically, top worst links are picked out by the index that is calculated by Eq.2.

$$Index = v/c_{lam} * (v_{lam}/T_{am}) + v/c_{lmd} * (v_{lmd}/T_{md}) + v/c_{lpm} * (v_{lpm}/T_{pm}) + + v/c_{lnt} * (v_{lnt}/T_{nt}) \qquad (2)$$

where T_{am} is the time duration at am; v/T aims at changing the unit of time duration to one hour. This index is created by making use of the traffic congestion index that is calculated by the average speed of the link that is weighted by traffic flow (Wang et al., 2009; Zheng & Chang, 2017). The *v/c* ratio reflects the road traffic congestion condition, and it is weighted by average flow across the four TODs (divided by time duration of four TODs) in this study to obtain the final index of each link. Different sets of toll links are picked out: top 25, 50, 100, 500, 1000 links, and seven bridges that go across the Colorado River. These seven bridges, where congestion often occurs, are the main corridor to connect the north and south sides of the river.

Optimum toll value on a link can be used as marginal external congestion cost, which is the difference between the marginal social cost (MSC) and the average cost (AC) (Smith, 1979; de Grange et al., 2017). MSC represents the marginal cost, which is the additional cost of adding one extra vehicle or trip to the traffic stream (Eq.3), and AC represents the average (private) cost (Eq.4) (Yang & Huang, 1998). Half of the difference, the original difference and twice the difference will be the toll values. These values will be analyzed (Eq.5) to determine which toll values work best on various links in the network. Assuming VOTT = $15/vehicle-hour that is used to change unit of time to cost. In each simulation iteration, the formal assignment results contain link travel time and traffic volume. In order to find the optimal toll for each link (the toll value should be adapted to the traffic flow on each link), toll values are updated based on previous iteration assignment results, and will be used for the next iteration (Sharon et al., 2016 & 2017), as Eq.6 shows.

$$MSC = \frac{\partial TT}{\partial v_l} = \frac{\partial (t_l \cdot v)}{\partial v_l} = t_l + \beta_l t_{FFT,l} \alpha_l \frac{v^{\beta_l}}{c^{\beta_l}} \tag{3}$$

$$AC = t_l = t_{FFT,l}(1 + \alpha_l \frac{v^{\beta_l}}{c^{\beta_l}}) \tag{4}$$

$$\tau_l = (MSC - AC) * VOTT = \beta_l t_{FFT,l} \alpha_l \frac{v^{\beta_l}}{c^{\beta_l}} * VOTT \tag{5}$$

where α_l and β_l are parameters of link *l* in BPR function, TT is the total travel time.

$$\tau_l^t = (1 - 1/n)\tau_l^{t-1} + 1/i * \tau_l \tag{6}$$

where *n* is the total number of iterations; τ_{t-1} is the toll value used in the iteration *t*-1; τ_t is the toll value used in the iteration *t*.

Similar to how travel time must be updated in the travel demand model, tolling values must also be updated in the travel demand model. Tolling values will be updated in the highway network of CAMPO in TransCAD. Both travel time and tolling may influence destination choice, mode choice and travel route choice. In addition, the route choice changes of travelers may affect traffic volume on each link, and thereby influence the travel time on each link. Therefore, toll value of each link should be adjusted to traffic volume on that link.

Traveler Welfare Calculations

Welfare changes due to tolling are used to evaluate policy effects. Small and Rosen (1981) refer to logsum differences as changes in consumer surplus or compensating variation (CV). This logsum method, used by De Jong (2007), Kalmanje et al (2009), Winkler (2016), and Ma and Kockelman (2016), is better than the rule of half method (rule of half assumes that the consumer demand (transport demand) curve is linear with respect to generalized costs), as it provides a comprehensive measure of impact across all destinations and modes (Kockelman et al., 2011). The expected maximum utility derived from all modes is calculated by Eq.7 (Kockelman et al., 2011).

$$\Gamma_{iu,d} = \ln[\exp(V_{iud,auto}) + \exp(V_{iud,bus})] \tag{7}$$

$$V_{iu,dm} = [\ln(Attr_d) - \ln(Attr_1)] + ASC_m - GC_{iu,dm} + \varepsilon_{iu,dm} \tag{8}$$

where Γ denotes expected maximum utility for an upper-level alternative; i is trip origin; u indexes the 5 traveler groups; d is trip destination; and V is the utility of each mode between each origin and destination; m represents modes type; $Attr_d$ is the attractiveness of each destination (measured in terms of employment, population and area at destination zone (Kalmanje et al., 2009); $Attr_1$ is the attractiveness of the any one TAZ which is a reference; ASC_m represents mode-specific constants (with 0 for automobile and -2.8 for bus); GC stands for each trip's total or generalized cost; $\varepsilon_{\text{iu,dm}}$ is an iid random error term from a Gumbel distribution.

Changes in consumer welfare or surplus (ΔCS) from one scenario to another for each traveler type can be computed as the logsum differences between those two scenarios. Here, those are computed with respect to the no-toll (base) scenario, as shown in Eq. 9 for HBNW and NHB trip purposes, and Eq. 10 for HBW trips (where travelers' work locations are assumed fixed, at least in the near term) (Lemp et al., 2009):

$$\Delta CS_{iu} = \frac{1}{\alpha_p}\{\ln[\sum_{d\in D}\exp(\Gamma^1_{iu,d})] - \ln[\sum_{d\in D}\exp(\Gamma^0_{iu,d})]\} \tag{9}$$

where D is the set of destination alternatives for HBNW and NHB trips and α_p is the marginal utility of money (Lemp et al., 2009).

$$\Delta CS_{iu} = \frac{1}{\beta_c}\{\sum_{d\in D} P^1(j\,|\,i)\exp(\Gamma^1_{iu,d}) - P^0(j\,|\,i)\sum_{d\in D}\exp(\Gamma^0_{iu,d})]\} \tag{10}$$

where β_c is the marginal utility of money (assumed to be 0.318 utils per \$1, as discussed in Lemp et al. (2009) and $P(j|i)$ is the probability of choosing destination j when the trip's origin is zone i.

The CBCP policy will benefit most or all travelers, after tolls are distributed to licensed drivers or any other budget-eligible population chosen by policymakers, in concern with citizen feedback. CBCP budgets or "credits" come from the toll revenues, minus tolling-system administrative costs, to enforce toll-tag accounts and to randomly audit system users. Such costs are assumed to be 10% of revenues, since technology costs are ushering in simpler ways of collecting tolls across large networks/everywhere. The remaining revenue would be returned to all licensed drivers (or other credit-eligible residents of the region) uniformly, to ensure equity in network access. Each licensed driver will receive a daily or monthly travel budget or "credit" (ρ = [\$/day/eligible traveler]), and this is split across the 3 trip purposes as follows:

$$\Lambda = \rho \cdot N_p / N \tag{11}$$

where N is average number of trips per day each person makes and N_p is average number of trips per person for trip purpose p each day. If ρ = \$1.50/day/eligible traveler, the average number of trips per day is 3.4, the average number of HBW trips is 1, then the credit given back to drivers for HBW trip is \$0.44/one trip /eligible traveler, and Λ will be added to ΔCS calculated by Eq.10.

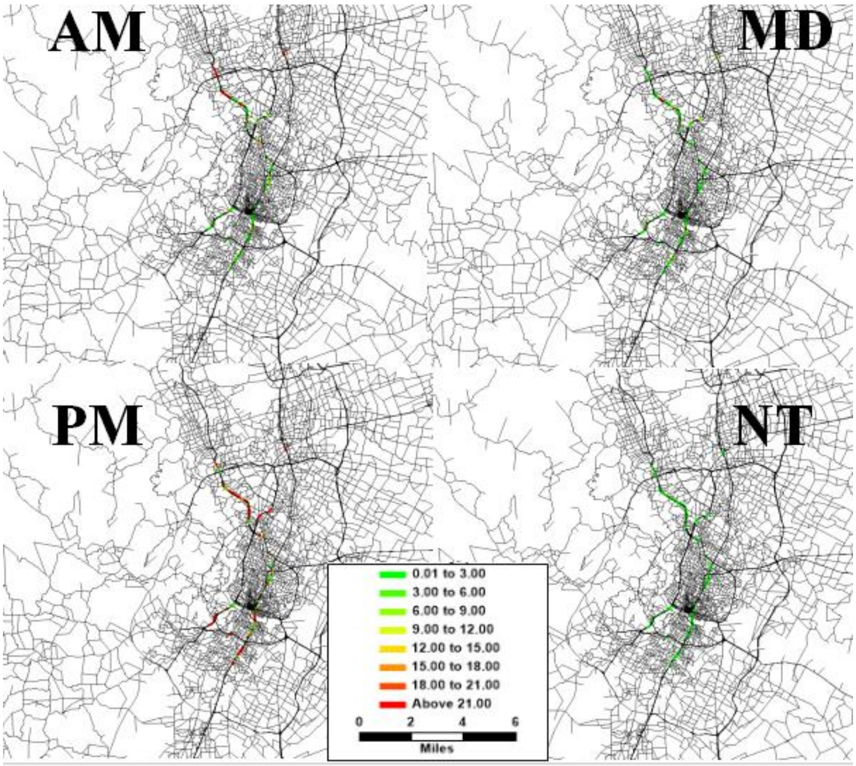
Though NHB trips do not link to a home location, there are spread across the region, and estimates of person-level welfare changes from each CP scenario are computed for each of the 5 VOTT categories across all of the region's 2,258 TAZs, to get a sense of each policy's welfare impacts over space and across traveler types, as described below.

The parameter values used in the methodology should be adjusted to meet the characteristics of the city analyzed. The city characteristics contain traffic and social conditions, trip characteristics, the highway network and so on. The values contain parameters used in the travel demand model, percentages of family income groups in each TAZ, VOTT of each traveler group, peak hour duration and so on. The analysis process and methodology can be replicated and validated by following the steps described in this section.

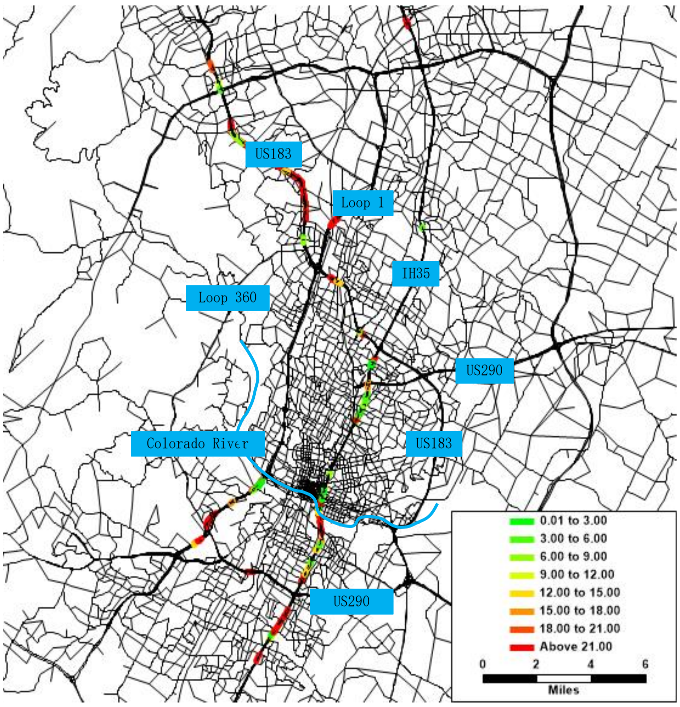
APPLICATION RESULTS AND DISCUSSION

Austin's CAMPO region covers 6 counties, with 2,258 TAZs and 25,176 links, with the total length being 9977.69 km. Caliper Corporation's TransCAD v 7.0 software and its GISDK code were used here to implement a four-step travel demand model. The analysis here assumes no real choice flexibility in departure times (across the four broad times of day use) and a gravity model for trip distributions. Although the Austin region already has 388 tolling stations (overhead gantries on relatively uncongested freeways, mostly far from the region's core), a no-tolling scenario is used here as the base case simulation. This straightforward base case helps one appreciate the levels of congestion and delay expected for year-2020 travel demands without any tolling. The top 100 links generating the most travel delay per mile of length over the course of a 24-hr weekday (under the base case conditions) were then identified, and the associated external costs of those delays (differences between total link travel time and a new user's travel time cost) per VMT are shown in Figure 1 (unit is cents per VMT) . The external costs of those delays are calculated by using the base case scenario's traffic assignment results (link travel time and traffic flow) (Eq.5).

CAMPO's network shows 388 links as already tolled in year 2020, with the same toll showing in peak and off-peak times of day. Using the base case traffic volumes on those links, times those flat toll rates, returns \$32.45 M in toll revenues per month (or \$1.27/day per person). Interestingly, the toll rates currently being charged are returning much higher revenues than the scenarios examined here would generate, across the entire network, except when tolling all links, especially outside the PM Peak time of day. These top 100-delay links include 36 of Interstate Highway 35's northbound links and 16 of IH35's southbound links, along with 28 links along US 183 N, 12 along Loop 1 South, 4 along Loop 1 North, 2 on US 183A, and 2 on US 290 W, with others scattered elsewhere. Assuming VOTT = \$15/vehicle-hour, the marginal social cost of delay per added vehicle on the worst link in the network during the AM peak period (7 to 9 am) is just τ = 60 cents/VMT (at a point on US 183 N). This max-toll value rises to 90 cents/VMT along Loop 1 North during the PM peak (3 to 7 pm). During the 6-hr MD and 11-hr NT hours, the delay values are so light on all 100 links that no congestion-based tolls are justified by the base-case traffic assignments.



(a) Top 100 Worst Links at Four TODs



(b) Top 100 Worst Links at PM and Labels of Important Roads

Figure 1. Toll Values on Worst Top 100 Links (in cents/VMT)

Altogether, 18 CP scenarios were simulated to compare to the base case (19th scenario), across 7 spatially distinctive settings: tolling the Top 25, Top 50, Top 100, Top 500, Top 1000, and all congested links, along with targeting only the 7 bridges (each direction) across the Colorado River that divides the Austin region through its mid-section, creating a series of important bottlenecks (at US 183S, IH 35, Loop 1 and Loop 360) that serve as substitute routing options for trips having origins and destinations on either side of the river. In all of these scenarios, less than 5% of the CAMPO-coded network (which is just 30%of the complete regional street + highways network) carries a toll, and only at peak times of day. So, most links in most locations are non-tolled, under any scenario. Tolling a subset of links can relieve congestion everywhere, if travelers are reasonably flexible in destination, departure time, mode and/or route choices.

The first set of 6 non-bridge-focused CP policies simply monetized the difference between the marginal travel time cost and average travel time cost curves from added vehicles on each link (as done in Kalmanje et al. [2009]). 13 other scenarios were also tested: 6 at double these rates and 7 at half these marginal-cost toll estimates. The argument for testing higher tolls is that most congested links are not being tolled under most scenarios. A double-toll approach helps reflect the fact that much of one's multi-mile car (or truck) trip is causing external delay costs on others (those behind us in the traffic stream but going untolled in these scenarios. Of course, another important objective in setting tolls is to avoid over tolling, since most of the network is not tolled in most of these scenarios, so there are normally many "free" substitute routes, and traffic may shift too far away from the tolled links, resulting in sub-optimal outcomes. Thus, 6 of the 18 CP scenarios used half-delay-cost tolls instead, to see if welfare effects could be improved with this type of simple "second-best policy". The final scenario was for bridge tolls only, and a simple $5 toll during AM and PM peak periods was used, in both directions, along with $3 MD and $0 NT bridge tolls, to keep things simple for travelers.

Travel Behavior and Network Impacts

Key performance metrics, like regional VMT, vehicle-hours traveled (VHT), distributions of volume-to-capacity (V/C) ratios, average travel speeds, and mode splits were computed here, for each scenario. These can help analysts obtain a sense of which polices can best approximate the first-best (all-congested-links tolled) scenario. Table 1 shows the VMT and VHT changes across the 6-county network before and after tolling, by time of day.

TABLE 1. Regional VMT and VHT Values across Seven Scenarios

VMT with 50% Marginal Cost Toll Rates								
VMT	**Base Case**	**Top 5 Links**	**25**	**50**	**100**	**500**	**1000**	**All Links**
AM	8,714K mi	8,726K	8,728K	8,728K	8,743K	8,735K	8,764K	8,847K
MD	12,915K	12,949K	12,949K	12,950K	12,949K	12,915K	12,918K	12,949K
PM	11,992K	12,014K	12,020	12,024K	12,036K	12,035K	12,103K	12,317K
NT	15,366K	15,366K	15,366K	15,366K	15,366K	15,366K	15,366K	15,367K
SUM	48,988K	49,056K	49,065K	49,070K	49,096K	49,053K	49,151K	49,481K
VMT with Marginal Cost Tolling								
VMT	**Base**	**--**	**25**	**50**	**100**	**500**	**1000**	**All Links**
AM	8,714K	--	8,722K	8,733K	8,750K	8,822K	9,012K	8,992K
MD	12,915K	--	12912K	12912K	12,913K	12,930K	13,000K	13,014K
PM	11,992K	--	12,024K	12,064K	12,087K	12,223K	12,599K	12,521k
NT	15,366K	--	15,366K	15,366K	15,366K	15,366K	15,366K	15,366K
SUM	48,988K	--	49,024K	49,076K	49,117K	49,342K	49,978K	49,893K
VMT with 200% Marginal Cost Tolling + 7 Bridges Scenario								
VMT	**Base**	**7 Bridges**	**25**	**50**	**100**	**500**	**1000**	**--**
AM	8,714K	8,793K	8,723K	8,736K	8,755K	8,835K	9,110K	--
MD	12,915K	12,964K	12,914K	12,912K	12,910K	12,920K	13,050K	--

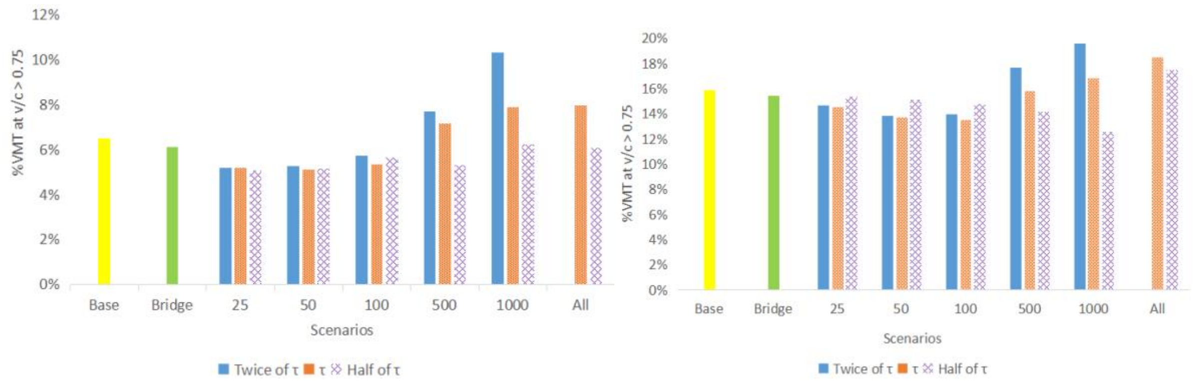
PM	11,992K	12,126K	12,031K	12,075K	12,101K	12,246K	12,779K	--
NT	15,366K	15,366K	15,366K	15,366K	15,366K	15,366K	15,366K	--
SUM	48,988K	49,250K	49,035K	49,091K	49,133K	49,368K	50,307K	--
VHT with 50% Marginal Cost Toll Rates								
VHT	**Base Case**	**5 Top Links**	**25**	**50**	**100**	**500**	**1000**	**All Links**
AM	349K hrs	355K	355K	355K	357K	350K	351K	357K
MD	484K	486K	486K	486K	486K	484K	484K	486K
PM	492K	500K	500K	499K	500K	493K	495K	505K
NT	572K	572K	572K	572K	572K	572K	572K	572K
SUM	1,898K	1,914K	1,914K	1,914K	1,916K	1,900K	1,902K	1,921K
VHT with Marginal Cost Tolling								
VHT	**Base**	**--**	**25**	**50**	**100**	**500**	**1000**	**All Links**
AM	349K	--	351K	351K	353K	350K	373K	364K
MD	484K	--	484K	484K	485K	488K	490K	487K
PM	492K	--	495K	496K	499K	514K	551K	516K
NT	572K	--	572K	572K	572K	572K	572K	572K
SUM	1,898K	--	1,902K	1,904K	1,908K	1,934K	1,987K	1,939K
VHT with 200% Marginal Cost Tolling + 7 Bridges Scenario								
VHT	**Base**	**7 Bridges**	**25**	**50**	**100**	**500**	**1000**	**--**
AM	349K	362K	350K	352K	354K	363K	391K	--
MD	484K	495K	484K	485K	485K	488K	495K	--
PM	492K	511K	496K	498K	501K	523K	584K	--
NT	572K	572K	572K	572K	572K	572K	572K	--
SUM	1,898K	1,941K	1,903K	1,907K	1,913K	1,946K	2,043K	--

As shown in Table 1, CP policies appear to add to VMT and VHT under all scenarios tested, though at relatively minor or moderate levels (ranging from 0.5% to 7% increases), versus the Base Case (no-toll scenario). The biggest increases come from the double-toll scenarios and Top 1000 link scenarios, which push many travelers – in most or all of the 5 VOTT classes - to longer routes, without having much effect on their destination choices, at least in the near term (when work and school trip patterns are largely fixed).

Mode shifts are even more moderate across all scenarios, with 93% to 96% to 95% of VOTT1 ($5/hr) travelers relying on personal cars and trucks for their HBW, NHB and HBNW trips in the base case, respectively. If the top 500 worst links are tolled, the percentages will change to 92%, 95% and 95%. While 98% of VOTT5 ($45/hr) travelers doing so for these three trip purposes, almost regardless of CP policy. Austinites' mode choices exhibit even more fixity than their destination choices. Only route choices seem malleable, making CP strategies tricky to implement under these modeling assumptions in this region.

Similarly, VMT-weighted averages of network speeds and V/C ratios suggest minimal shifts, excepting peak periods of day, when average V/C ratios fall by a few percentage points under the Top 1000 and All Links Tolled scenarios. Since V/C values over 0.77 are often considered "congested" (Boarnet et al., 1998), the shares of VMT on the CAMPO-coded network that experienced such V/C ratios were computed across the 19 scenarios. The shares of VMT are calculated by three steps: (1) Selecting out links with v/c larger than 0.75; (2) Summing the VMT of these links; (3) Calculating the percentage of VMT. There were important drops in the shares of high V/C ratios in the AM Peak (from 7% of all AM PK

VMT to 5%, for example), but roughly 15% of PM Peak VMT stayed at the 0.77+ V/C ratio under most CP scenarios, shown in Figure 2.



(a) AM (b) PM

Figure 2. VMT Percentages Changes at v/c > 0.75 for Different Scenarios (Yellow Bar Represents the Base Case)

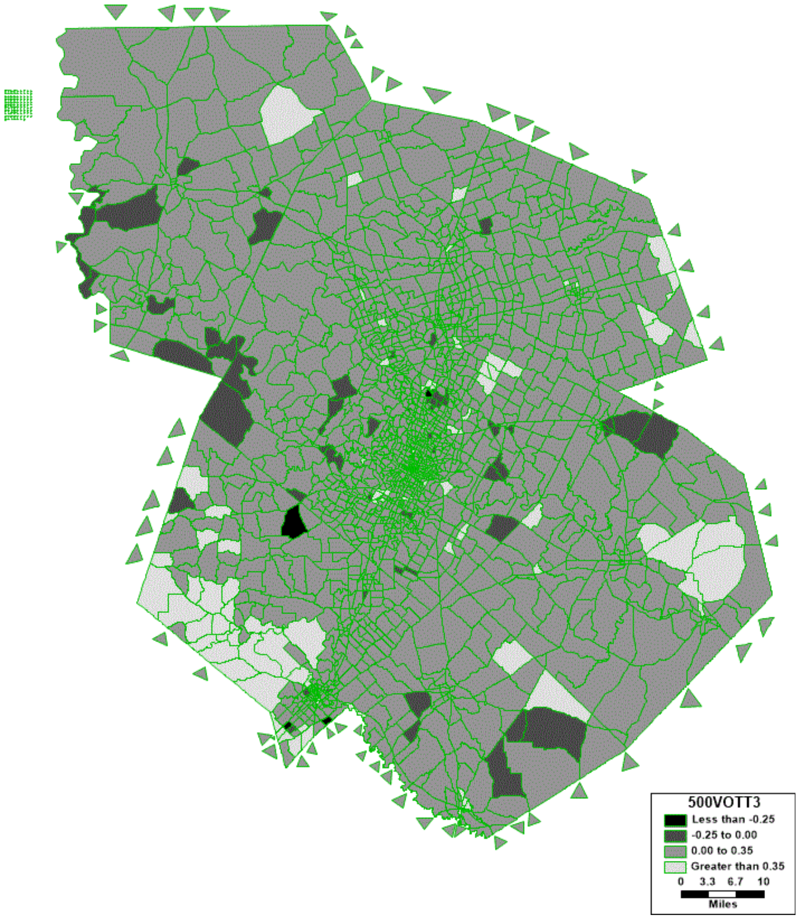
Welfare Impacts

This section brings the idea of CBCP into the welfare impacts assessment. Table 2 shows estimates of toll revenues each day, with a column for tolls minus 10% administrative expenses (to manage the system), to provide a total budget to distribute equitably across Austin's 1.16 million licensed drivers in year 2020. CP revenue estimates rise from just $164,392 per day when tolling only the 25 most delay-inducing links to $1.88 million per day when tolling all congested links across the CAMPO-coded network. Table 2 also reflects the added delays induced by the marginal vehicle on those links, across 4 times of day (with NT tolls at $0 everywhere). The resulting travel credits (assigned to all of the region's licensed drivers equally) would thus range from $16.65/month/person to $65.12/month per person, or $35.57 per month under the 7-tolled-bridges scenario. These all appear as reasonable travel "budgets" for those able to drive along the region's roadways. Those who do not need their credits can donate them to special cases (single, working parent households who apply for special compensation, due to long work journeys at peak times of day). And visitors to the region (or anyone driving without a toll tag account) can be admitted freely up to a certain number of passes per month, in front of camera stations, where license plate recognition processes would lead to pay-by-mail toll collection.

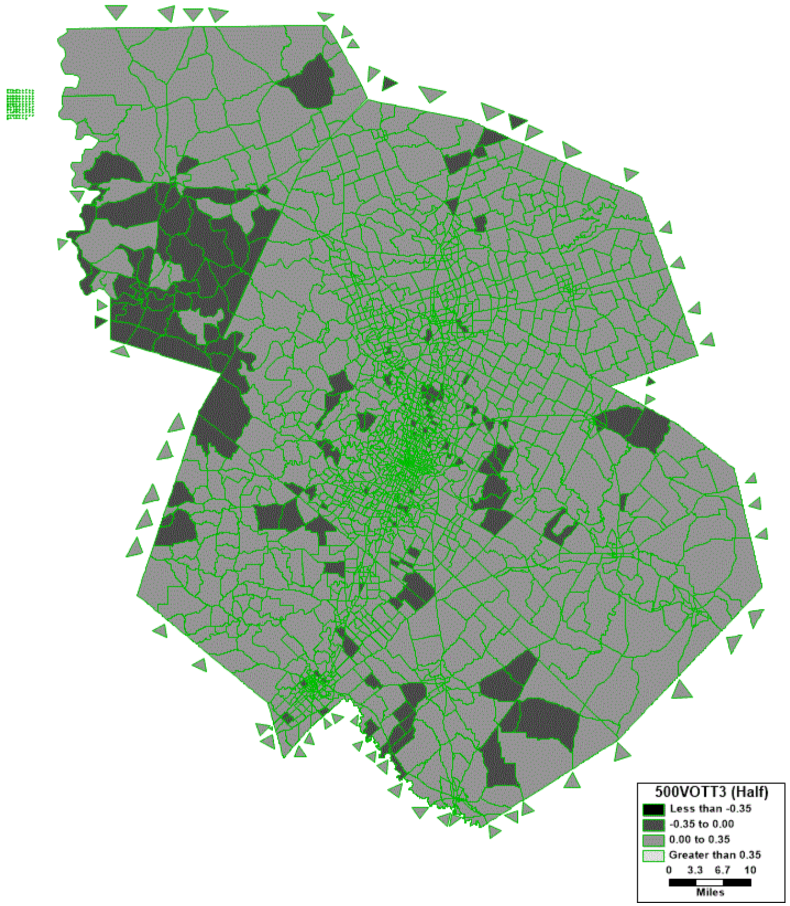
TABLE 2. Estimates of Tolls Revenues and Travel Credits across Scenarios

	AM Peak Toll Revs. per Day	MD (mid-day) Toll Revs. per Day	PM Peak Toll Revs. per Day	**Total Toll Revs.** per Day	Total **Credits for Distrib.**	Credits per Driver per Day	**Credits per Driver per Month**
7 Bridges	$312.16K	$267.6K	$396.05K	$975.8K	$0.88M	$0.76/day	$16.65/mo.
25	$39.19K	$12.65K	$130.82K	$182.66K	$0.16M	$0.14/d	$3.12/mo.
50	$73.45K	$25.09K	$217.92K	$316.46K	$0.28M	$0.24/d	$5.40/mo.
100	$124.29K	$36.23K	$284.74K	$445.28K	$0.40M	$0.34/d	$7.60/mo.
500	$420.48K	$117.11K	$857.04K	$1,394K	$1.26M	$1.08/d	$23.82/mo.
1000	$1,164K	$255.78K	$2,395K	$3,815K	$3.43M	$2.96/d	$65.12/mo.
All Links	$571.56K	$128.87K	$1,383K	$2,083K	$1.88M	$1.61/d	$35.57/mo.

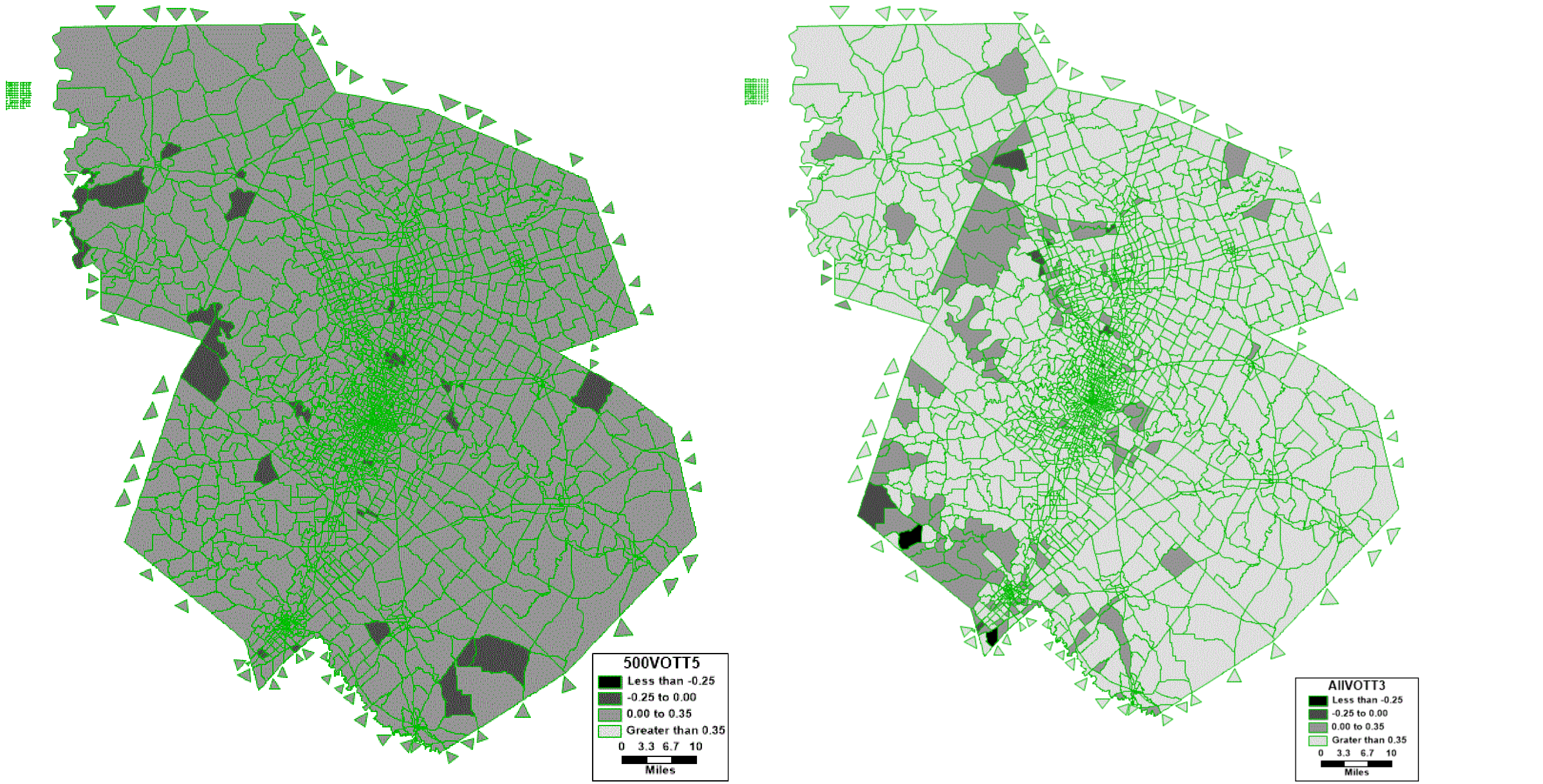
Due to the content limitation, this research takes HBW trip purpose as an example to evaluate typical welfare changes under a CBCP policy. Figure 3 maps show expected variations in consumer surplus changes (ΔCS) across policies and across Austin TAZs for the VOTT3 ($25/hr) and VOTT5 ($45/hr) classes.



(a) 500 links VOTT3 (200% Marginal Cost Tolling)



(b) 500 links VOTT3 (50% Marginal Cost Tolling)



(c) 500 links VOTT5 (200% Marginal Cost Tolling) **(d) All Congested Links Tolled VOTT3 (MC Tolling)**

Figure 3. Predicted Welfare Changes for Travelers with HBW Trip Purpose during AM Peak Period

Under the 200% Marginal Cost Tolling assumption for the Top 500 (most delay-inducing) links (Fig 3a), 97% of the region's TAZs' VOTT3 travelers are estimated to benefit from the CBCP policy, while 98.5% of TAZs' VOTT5 benefits (Fig 3c). Those whose work trips originate in the region's far northwest or southern locations are estimated to face losses, on average, under this scenario, but the regional boundary is not realistic, and such travelers often have work trips elsewhere that may not be affected by the tolling policies or may be too short to matter, largely outside this 6-county region (as discussed by Gulipalli et al. (2007) for CBCP simulations in the DFW region). Under the 50% MC tolling assumption for the Top 500 links (Fig 3b), the losses are estimated to expand over these low-density TAZs, especially in the region's northwest locations, so just 91% of the region's TAZs have travelers expected to benefit, which is still a sizable share when one is trying to address all the inequities and serious economic and other losses that come with congested and unreliable networks. There are also strong cases to be made for the VOTT1, VOTT2 and VOTT4 traveler classes, especially towards the regional core, where congestion abates. Therefore, under these cases, important expected-travel time savings and travel time reliability benefits emerge, helping deliver people (and packages and services) to their destinations in a timelier and less stressful way.

CONCLUSIONS

To alleviate traffic congestion with the objective of benefiting the most travelers, this work simulates the impacts of many CBCP policies across the 6-county Austin region in Year 2020. Personal travel demands were estimated for three different trip purposes, across 5 VOTT traveler classes, 2258 TAZs, and 4 times of day. Congestion tolls were applied to the Top 25, 50, 100, 500, and 1000 highest delay-cost links in the network to reflect marginal delay costs on just those links, and then at half and then double those levels, to appreciate traffic and welfare changes. Flat tolls by time of day were also placed on the Colorado River's 7 bridges, to see if that would avoid route-circuity effects witnessed in the other scenarios. This study aims to determine which tolling strategy combinations (number of tolling links and tolling values) can achieve a harmonic relationship between decreasing traffic congestion and improving travelers' welfare. Tolling heavy on each link may increase travelers' welfare but may create new congested links and make traffic worse. Although tolling less on the links may not cause much negative impact on the traffic network, travelers' welfare will be weakened.

With the increase of tolling links, the VMT and VHT increase, especially when tolling twice of the τ. Higher tolling values (twice of τ) decrease the average speed (VMT weighted) while decreasing the v/c (VMT weighted). The scenario that tolls 1000 links saw an average speed decrease of about 3% when tolling twice of τ, which is much worse than tolling half of τ or τ. The percentage of VMT with v/c > 0.75 was also worse than other scenarios, especially when tolling twice of τ on 1000 links. Tolling τ in different scenarios shows a similar trend to tolling twice of τ in different scenarios, while they show more positive influence on the traffic condition, most of the V/C (VMT weighted) decrease most, average speeds (VMT weighted) decrease less or increase more. Compared to other scenarios, tolling 500 links shows a better effect, with a small decrease of v/c (VMT weighted), increase or small decrease of average speed (VMT weighted) and small changes of percentage of VMT with v/c>0.75.

Under the seven scenarios, tolling twice of τ on 500 links will benefit 96.59% of TAZs' VOTT 3 travelers and 98.54% of TAZs' VOTT 5 travelers. Compared to tolling half of τ, tolling twice of τ will benefit more people, although tolling too much on several links will worsen other links or create new congested links, so, in order to achieve a better traffic condition and a better welfare for travelers at the same time, travel demand models should be simulated to achieve a balance between the two. Tolling on the entire network will see

99.33% of TAZs' travelers benefit from the CBCP policy, which is the best case of all the tested tolling scenarios.

In summary, if tolling several links in the network, it is necessary to simulate better toll values and avoid creating new congestion spots or links. In order to make simulation more realistic, it is crucial to consider the time of day shift in the travel demand model in a real network, because some travelers will shift their departure time to avoid the tolling at peak time. Most of the former researches used a virtual network to simulate which need to be more practical.

ACKNOWLEDGEMENTS

The authors are grateful for Albert Coleman's editing support, and financial support of the China Scholarship Council, which funded the lead author's one-year stay in the U.S.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: K. Kockelman. Data assembly and model specification: W. Li and Y. Huang. Analysis and interpretation of results: W. Li and K. Kockelman. Draft manuscript preparation: W. Li, K. Kockelman, and Y. Huang. All authors reviewed the results and approved the final version of the manuscript.

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