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

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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 feedback are used to deliver inputs for normalized logsum differences to quantify and compare consumer surplus changes across traveler types, around the region. 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, 95.04% TAZs’ VOTT group 1 will benefit from the CBCP.

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 alleviate it (Vickery, 1969; Vehoef et al., 2000; Yang, 2000), through influences on user’s 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, which however
can be compensated with less travel time, reduced fuel cost, and lower level of driving stress
at congestion (Stefanello, et al., 2017), along with decreased vehicle-hours traveled (VHT)
and vehicle-miles traveled (VMT), and increased consumer surplus (Gupta et al., 2006).

After first 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 merits during its
implementation, but many disadvantages have been revealed, although Van den Berg and
Van & Verhoef (2011) indicated that CP can improve social welfare of the majority of (55%
in first-best pricing) travelers (even without returning toll revenues to them), the
implementation effects of CP depend largely on drivers’ acceptability and responses (Gibson
et al., 2015) because of the equity and fairness issues (Eliasson et al., 2016). This policy often
rejected by the public because it is considered as an additional tax (Cipriani et al., 2019) and
unfair for traveler groups with lower income. With CP, road users with high value of travel
time (VOTT) are more willing to pay to experience less travel delay, while low VOTT road
users have to shift their travel mode, departure time or routes to avoid paying tolls and lose
the rights to use road at peak hours. This results in the redistribution of traffic throughout the
network. Travelers perceiving different VOTTs present different travel behavior in response
to CP, reflected by destination choice, departure time choice, route choice and mode choice.
Arnott et al. (1988) and Lindsey (2004) pointed 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 acceptability of CP policy, users
should benefit from the policy (Adler et al., 2001). Credit-based congestion pricing (CBCP)
policy is then 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 less, or
even make some money, while those who still travel at peak hours or travel long distance will
pay money. Kockelman and Kalmanje (2004) concluded that CBCP may provide the most
 equitable and efficient implementation alternative and have the potential to alleviate traffic
congestion and benefits most of the region and travelers. In 2005, Kockelman and Kalmanje
(2005) polled the public in Austin, TX, and found that CBCP may 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
given the state of technology and congestion in many urban regions, CBCP may now be
viable both politically and technologically. 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 just those along
major highways, relative to the status quo scenario. They estimated that 50%-65% of
travelers in that 9-county region would benefit from the CBCP policies tested, while
removing all points of heavy congestion (excepting 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 time of days (AM, mid-day
(MD) and PM). Recognizing just two groups of travelers (those with high VOTT versus low
VOTT), they estimated how travelers would be better off if one of the routes to the distant
destination operated under a CBCP policy, especially for travelers with low VOTT.

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 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 past and many current settings (Kockelman et al., 2011; Gholami, et al., 2015; Cheng et al., 2019, Cipriani et al., 2019). As noted by Zhang and Ge (2000 & 2004), first-best toll applications can significantly increase information and uncertainty burdens on users, resulting in political resistance to its implementation. Many thoughtful versions of second-best pricing can harmonize system efficiency gains, system investment and operating costs (Johansson & Sterner, 1998). As one example, Gupta et al. (2006) founds that it may be wise to price only Austin’s bridges during peak times of day to achieve much consumer surplus gain and dramatically relieve that region’s congestion, rather than applying MCP at all congested times of day on all bridges.

Most CBCP research to date (Gulipalli & Kockelman, 2008; Kalmanje & Kockelman, 2009; Lemp & Kockelman, 2009) has focused on freeway tolls, due to the real cost of toll collection using past technologies. And most CP research has focused on small and generic networks (Verhoef et al., 2002 & 2010; Yang et al., 2003; Zhang et al., 2004; Koh et al., 2009), with many calculations and optimizations difficult to apply 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, the work first identifies the most “congested” (i.e., delay-inducing, due to high travel and high delays) 500 links among Austin’s 25,176 coded roadway links. To see if limited tolling applications may be helpful, the work simulates the impacts of tolling the worst 25 links, then the worst 50, 100, 500, and 1000 links in this network, in terms of their delay effects. Since those applications mostly add VMT and VHT (as motorists largely shift to more circuitous routes), the work compares the effects of tolling the regions 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 CAMPO uses in its trip-based models. In all scenarios, travelers are sorted across 5 VOTT classes (from $5/hr to $45/hr, in steps of $10/hr), with 3 trip purposes: home-based work [HBW], home-based non work [HBNW] and non-home based [NHB] trips. Just 2 modes are used (automobile and bus) and four time of days (AM, PM, MD [midday], NT [night]). After model simulation, traffic and welfare impacts of these strategies are compared and analyzed. More details on methods and results are provided below.

**METHODOLOGY**

This section gives the methodologies used in this paper to simulate and analyze the influence of CBCP policy, which contain the travel demand model, methods used to calculate toll values, pick out the top 500 worst links and calculate welfare changes.

**Travel Demand Model**

Travel demand model used in this paper is a traditional four-step model, including trip generation, trip distribution, and mode choice, time of day and traffic assignment. To evaluate the influence of CBCP on the travel pattern and road condition, travelers are divided into five VOTT groups from $5/hr to $45/hr ($5/hr, $15/hr, $25/hr, $35/hr and $45/hr). Each VOTT groups correspond to one income group (CAMPO travel demand model divided the
household income in a year to five groups and provided the percentage of each groups in each TAZs. Trips made by these five VOTT groups in each TAZ are also identified by three trip purposes. For trip generation, HBW and HBNW trips produced from a VOTT group are determined by the population share of the corresponding income groups among total trip production in every traffic analysis zone (TAZ). NHB trips produced by five VOTT groups are assumed to be evenly distributed. Trip productions in each TAZ are calculated by income per household (medial income) and household auto ownership (0, 1, 2, or 3+), and trip attraction in each TAZ are calculated by retail and non-retail employment in the TAZ by using Quick Response Method (QRM) in TransCAD 7.0, and the data needed are obtained from CAMPO model directly. Trip generation results will obtain 15 tables of production and attraction for five VOTT groups by three trip purposes. After that, trip distribution is implemented separately for each VOTT group by purposes. Impedance function (Gamma function) use the time of shortest path as the impedance which consider the influence of the toll value. A binary logit mode choice model is then conducted considering only two modes (automobile and bus) for five VOTT groups using different VOTTs, which are reflected from the utility function. Automobile utility is calculated based on cost and in-vehicle travel time (IVTT) of the five user groups, and the utility of bus is calculated by fare and IVTT. Automobile’s cost contains operating cost and parking cost at the destination. Model specifications for mode choices are adopted from Yong and Kockelman (2018), Parameters of automobile are distinct for five VOTT groups (IVTT: -0.019; cost: -0.228, -0.076, -0.0456, -0.033, -0.025 for five VOTTs), but parameters of bus are the same (IVTT: -0.019; cost: -0.14.).

Fifteen production-attraction tables (for five VOTTs groups and three trip purposes separately) are obtained from mode choice, while time of day procedure transforms them into 15 origin-destination tables. Time of day is 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). A multi-modal multi-class traffic assignment (MMA) was carried out for the region’s two modes: automobile (5 VOTT groups and 3 trip purposes) and commercial trucks. The commercial truck trip table is obtained from CAMPO model directly.

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

\[ t_i = T_{FFT}(1 + \alpha(v/c)^\beta) \]  

where \( t_i \) is the travel time on link \( l \), \( T_{FFT} \) is the free flow travel time on link \( l \), \( v \) is the traffic flow on link \( l \), \( c \) is the capacity of link \( l \), alpha and beta parameters are obtained from CAMPO model. Travel time and tolling results in each MMA will feedback to the next iteration until they remain stable. 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 looking at the value of \( v/c \) multiplied by travel demand, while demand is calculated by VMT on this link divided by link length and travel time. Indices of four TODs are summed as the final index to pick out the worst set of links that need tolling. Different sets of toll links are picked out: top 25, 50, 100, 500, 1000 links, and seven bridges that go across Colorado River. These seven bridges, where congestion often happens, are the main corridor to connect north side and south side 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). Half of the difference, difference and twice of the difference will be chosen to be the toll value and analyzed the better values to be tolled on the picked links and
their influence (Eq.2), because the uncertainty about the which toll values are better when
tolled on several links in the network. In the model simulation and each iteration, the formal
assignment results which contain the link travel time, traffic volume of each link and so on, in
order to find a better toll for each link, toll values are updated according to the previous
iteration assignment results will be used for the next iteration (Sharon et al., 2016 & 2017), as
the Eq.3 shows.

\[ \tau_i = MSC - AC = \beta_i^{\text{FFT}}, \alpha_i \frac{v_i^{\beta_i}}{c_i} \]  
(2)

where MSC is marginal social cost; AC is average cost to the user, \( \beta_i \) is parameter of link \( l \) in
BPR function.

\[ \tau'_i = (1 - 1/i)\tau^{i+1} + 1/i \tau_i * VOTT \]  
(3)

where \( i \) is the number of iterations, \( \tau^{i+1} \) is the toll value used in the last iteration, and \( \tau' \) is the
toll value used in next iteration.

### 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), Ma
and Kockelman (2016), to be better than the rule of half method (RoH 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 destination and modes (Kockelman et
al., 2011). The expected maximum utility derived from all modes are calculated by Eq.4.

\[ \Gamma_{iu,d} = \ln[\exp(V_{iu,\text{auto}})] + \exp(V_{iu,\text{bus}})] \]  
(4)

\[ V_{iu, dm} = [\ln(\text{Attr}_d) - \ln(\text{Attr}_1)] + ASC_m - GC_{iu, dm} + \epsilon_{iu, dm} \]  
(5)

where \( \Gamma \) 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; \( \text{Attr}_d \) is the attractiveness of each
destination (measured in terms of employment, population and area at destination zone
(Kalmanje et al., 2009); \( \text{Attr}_1 \) 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; \( \epsilon_{iu, dm} \) is an iid random error term from a Gumbel
distribution.

Changes in consumer welfare or surplus (\( \Delta CS \)) 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. 6 for HBNW and NHB
trip purposes, and Eq. 7 for HBW trips (where travelers’ work locations are assumed fixed, at
least in the near term):

\[ \Delta CS_{iu} = \frac{1}{\alpha_p} \{ \ln[\sum_{d \in D} \exp(\Gamma^{1}_{iu,d})] - \ln[\sum_{d \in D} \exp(\Gamma^{0}_{iu,d})] \} \]  
(6)

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

\[ \Delta CS_{iu} = \frac{1}{\beta_c} \{ \sum_{d \in D} P^{1}(j \, | \, i) \exp(\Gamma^{1}_{iu,d}) - P^{0}(j \, | \, i) \sum_{d \in D} \exp(\Gamma^{0}_{iu,d}) \} \]  
(7)
where $\beta_c$ 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 sought is one that 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 randomly audit system users, for example. 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 revenues 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” ($\rho =$ [$/\text{day/eligible traveler}]$, and this is split across the 3 trip purposes as follows:

$$\Lambda = \rho n / n_p$$  \hspace{1cm} (8)

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 $\rho =$ $1.50$/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, which will be added to $\Delta CS$ calculated by Eq.7.

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 is computed for each of the 5 VOTT categories across all of the region’s 2,258 traffic analysis zones (TAZs), to get a sense of each policy’s welfare impacts over space and across traveler types, as described below.

**APPLICATION RESULTS AND DISCUSSION**

Austin’s CAMPO region covers 6 counties, with 2,258 TAZs and 25,176 links. 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 that no real choice flexibility in departure times (across the four broad times of day use), a gravity model for all trip distributions, and $8.14$/hr VOTT for all bus users. 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 (in cents per VMT) using this base case scenario’s traffic assignment results.

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 $32.45 \text{ M}$ 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 $\tau = 60$ 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 these 100 links that no congestion-based tolls are justified by the base-case traffic assignments.

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

All together, 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, Lamar Blvd, Pleasant Valley Rd, Loop 1, Redbud Trail 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], for example). 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, for example) 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 direction, 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 policies 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**

<table>
<thead>
<tr>
<th>VMT</th>
<th>Base Case</th>
<th>Top 5 Links</th>
<th>25</th>
<th>50</th>
<th>100</th>
<th>500</th>
<th>1000</th>
<th>All Links</th>
</tr>
</thead>
<tbody>
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<td>AM</td>
<td>8,714K mi</td>
<td>8,726K</td>
<td>8,728K</td>
<td>8,728K</td>
<td>8,743K</td>
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<td>12,949K</td>
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<td>12,020K</td>
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<td>SUM</td>
<td>1,898K</td>
<td>1,914K</td>
<td>1,914K</td>
<td>1,914K</td>
<td>1,916K</td>
<td>1,900K</td>
<td>1,902K</td>
<td>1,921K</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>VHT</th>
<th>Base Case</th>
<th>7 Bridges</th>
<th>25</th>
<th>50</th>
<th>100</th>
<th>500</th>
<th>1000</th>
<th>All Links</th>
</tr>
</thead>
<tbody>
<tr>
<td>AM</td>
<td>349K</td>
<td>351K</td>
<td>351K</td>
<td>353K</td>
<td>350K</td>
<td>350K</td>
<td>373K</td>
<td>364K</td>
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<tr>
<td>MD</td>
<td>484K</td>
<td>484K</td>
<td>484K</td>
<td>485K</td>
<td>488K</td>
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<td>490K</td>
<td>487K</td>
</tr>
<tr>
<td>PM</td>
<td>492K</td>
<td>495K</td>
<td>496K</td>
<td>499K</td>
<td>514K</td>
<td>514K</td>
<td>551K</td>
<td>516K</td>
</tr>
</tbody>
</table>
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 1000-Top 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% of VOTT1 ($5/hr) travelers relying on personal cars and trucks for their HBW and NHB trips, respectively, and 98% of VOTT5 ($45/hr) travelers doing so, 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, expecting 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. 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.

![Figure 2. VMT Percentages Changes at v/c > 0.75 for Different Scenarios (Yellow Bar Represents the Base Case)](a) AM  (b) PM

Welfare Impacts

Table 2 shows estimates of tolls 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, at prices designed to reflect 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

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

Using the HBW trip purpose 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 TAZ 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)
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 regions’ TAZs’ VOTT3 travelers are estimated to benefit from the CBCP policy, while 98.5% of TAZs’ VOTT5 benefits (Fig 3c). Figure 3 (a & c)). Those whose work trips originate in the region’s far northwest or southern locations are estimate 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, so important expected-travel time savings and travel time reliability benefits emerge, helping deliver people (and packages and services) to their destinations in a more timely and less stressful way.

**CONCLUSIONS**

To alleviate traffic congestion with an 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 may avoid route-circuitity effects witnessed in the other scenarios.

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 decrease the v/c (VMT weighted). The scenario that tolling 1000 links will see the average speed decrease about 3% when tolling twice of τ, much worse than tolling half of τ or τ, the percentage of VMT with v/c > 0.75 also worse than other scenarios, especially when tolling twice of τ on the 1000 links. Tolling τ on different scenarios show the similar trend with twice of τ tolled on 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, the scenario that tolling 500 links show a better effect, with 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, Twice of the τ are tolled on the 500 links will benefit 96.59% TAZs’ VOTT 3 travelers and 98.54% TAZs’ VOTT 5 travelers. Compared to half of the tolling, twice of the τ will benefit more people, although tolling too much on several links will worse other links or created 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 and achieve a balance between the two. Tolling on all the network will see 99.33% of TAZs’ travelers benefit from the CBCP policy, which will benefit the most TAZ travelers compared to any other 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.

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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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