Personalized Pareto-improving Congestion Pricing and Tradable Credit Schemes

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Short summary

Equity is a key issue that hampers public acceptability of congestion pricing. Although revenue refunding and tradable mobility credit (TMC) schemes offer a means to redress issues of equity, they cannot guarantee Pareto-improvement (i.e., no user is worse off) when toll revenues are uniformly redistributed (or credits in the case of TMCs). In this paper, we develop a bi-level optimization framework for both pricing with personalized revenue refunding and TMCs with personalized credit distribution that are efficient, equitable, and Pareto-improving. The system optimization level determines the tolling policy while the user optimization level determines an individual-specific refunding of revenue (or distribution of credits for TMCs). Simulation experiments for the morning commute problem in a combined mode and departure time context (with heterogeneity and non-linear income effects) demonstrate that the proposed approach can make congestion tolling Pareto improving and more equitable while attaining desired improvements in network congestion and welfare.
Keywords: Congestion pricing, tradable credits, equity, revenue recycling

1 Introduction

Traffic congestion is a pressing issue that imposes significant costs on the economy, environment and society. Congestion pricing is widely recognized as being an effective means of managing congestion (Lindsey & Verhoef, 2001; de Palma & Lindsey, 2011) and can influence the entire spectrum of travel decisions including trip generation, departure time, mode and destination choices (de Palma & Lindsey, 2011). Successful implementation of congestion pricing schemes include Singapore's Electronic Road Pricing Scheme (ERP), London's Congestion Charge (CC), and Stockholm's Congestion Tax.

However, the issue of equity remains one of several challenges to the successful implementation and acceptance of congestion pricing as evident in the failures of previous attempts in Greater Manchester, Edinburgh and New York City. One of main reasons is that the out-of-pocket charges of congestion pricing disproportionately hamper low-income users from using road facilities and make road usage a privilege of high-income users (Lindsey & Verhoef, 2001; Gu et al., 2018).

Studies (Jaensirisak et al., 2003) have indicated that congestion pricing can be more acceptable if it increases everyone's benefit (termed Pareto-improving) besides the overall net social benefit (welfare). Two means of achieving this are first, revenue recycling or refunding schemes (Small, 1992) which simply involve a re-distribution of toll revenues back to users and second, tradable mobility credit schemes (TMCs), which are a hybrid form of price and quantity control (Grant-Muller & Xu, 2014). In TMCs, the issue of equity can be addressed through the initial distribution of mobility credits.

The literature has shown that in the case of congestion pricing, refunding toll revenues uniformly to users does not guarantee Pareto improvement (see Small (1992); Arnott et al. (1994)). Revenue refunding schemes and the conditions under which Pareto-improvement may be possible have been widely studied using both network equilibrium and bottleneck models (Nie & Liu, 2010; Xiao & Zhang, 2014; Guo & Yang, 2010). Thus, some form of personalization is necessary to guarantee that both the pricing and TMC schemes are Pareto-improving. Literature on personalized pricing in the transportation field is limited, but applications can be found in the airline industry, where personalized fare offers based on estimated WTP have been implemented (Wittman & Belobaba,

2017). Zhang (2019) develop personalized discounting policies for managed lane tolling; other applications of personalization in transportation include the provision of incentives to promote sustainable behavior (Azevedo et al., 2018; Xie et al., 2020).
In this paper, we attempt to address the aforementioned equity issues by proposing a bi-level optimization framework for both pricing with personalized revenue refunding and TMCs with personalized credit distribution that guarantees Pareto improving outcomes.

2 Methodology

We first describe the problem context and simulation approach, followed by the optimization framework in three parts: pricing with no refunding, pricing with uniform refunding and pricing with personalized refunding. Finally, we discuss how these formulations can be utilized to determine a personalized allocation of credits for TMC schemes.

Context and simulation framework

The simulation framework builds upon Chen et al. (2023), which we summarize briefly. We consider N travelers who commute daily between a single origin-destination pair. For simplicity, each traveler has a single morning trip explicitly simulated, and their evening trip is assumed to mirror the morning trip. We consider a standard bi-modal transportation network (similar to Liu & Szeto (2020)) where travelers choose between driving and a public transit alternative. If they drive, they use a path containing a bottleneck of fixed capacity and choose their time of departure. We do not consider the departure time dimension for the transit alternative.

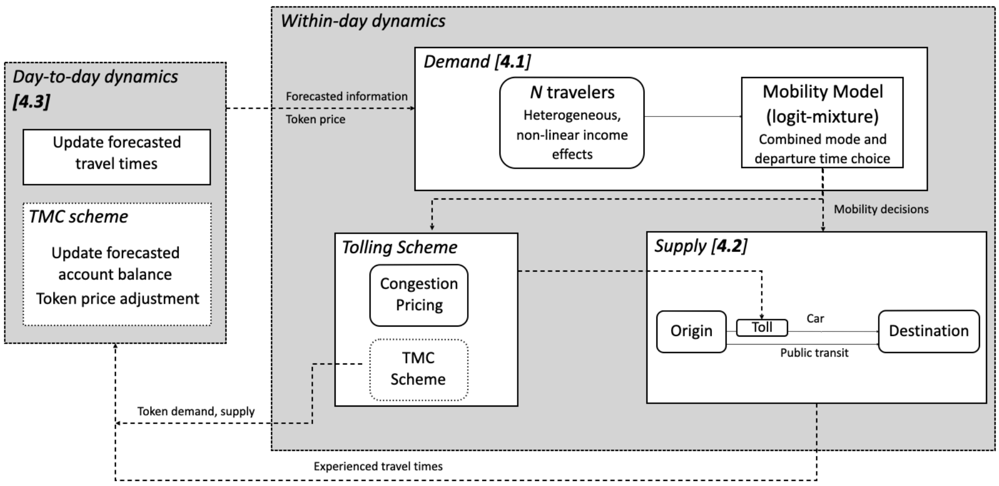


Figure 1: Modeling and simulation framework

At the beginning of each day, travelers use forecasted information on travel times, schedule delays, and account balance (TMC only) to make a *pre-day mobility decision*. This decision involves choosing a mode (car or public transit) and a departure time for the morning commute trip. Travelers opting to drive may encounter a time-of-day toll (charged in either dollars or mobility credits). The individual mobility decisions are modeled using a logit mixture model that allows for heterogeneity and non-linear income effects.
The mobility decisions are simulated on a simple network with a single driving path and an alternative public transit (PT) line. Congestion for driving is modeled by a standard bottleneck model, in which a queue develops once flow exceeds capacity. Public transit travel time is assumed to be constant.
Day-to-day dynamics is modeled through an exponential smoothing filter to update forecasts of travel time and account balance (TMC) throughout the day. The simulation framework in Figure 1 is used to simulate the evolution of the system state (departure flows, travel times) until convergence is reached. Performance measures such as overall welfare, user benefits, and congestion are evaluated at convergence. The model is a doubly dynamical system, which considers the day to day evolution of a within-day dynamic system involving departure-time and mode choices.

We next describe the demand model, which captures the combined decision of choosing a depature time and mode. The day is discretized into $h = 1 \dots H$ time intervals of size Δ_h (let the set of all time intervals in the day be denoted by $\mathcal{H} = \{1, \dots, h, \dots, H\}$).
Each individual n has a choice set of mode defined as $M_n = \{C, PT\}$ (C for car and PT for public transit) and a set of feasible departure time intervals $\mathcal{H}_n = \{\tilde{t}_{0n} - \eta\Delta_h, \tilde{t}_{0n} - (\eta - 1)\Delta_h, \dots, \tilde{t}_{0n} + \eta\Delta_h\}$ consisting of 2η time intervals of size Δ_h centered around the preferred departure time interval on day 0, $\tilde{t}_{0n}$. $\tilde{t}_{0n}$ is computed based on the preferred arrival time $\hat{t}_n$ and the free flow travel time.
The set of feasible departure time intervals under instrument j ($j = NT, P, M$ for the No Toll scenario, congestion pricing, and the TMC scheme respectively), is denoted $\mathcal{H}_n^j \subseteq \mathcal{H}_n$. Under the No Toll scenario, $\mathcal{H}_n^{NT} = \mathcal{H}_n$. For the transit alternative, we consider only one departure time interval that will result in an arrival time closest to the preferred arrival time. This is denoted by h_n^{PT}. Let $i = \{m, h\} \in \mathcal{I}_n$ represent an individual's mobility decision (where $\mathcal{I}_n = \{C, h | h \in H_n^j\} \bigcup \{PT, h_n^{PT}\}$).
The money-metric utility of an individual n driving and departing in time interval h (choosing $i \in \{C, h | h \in H_n^j\}$) under instrument j is defined as,

$$\begin{aligned} U_{in}\left(\tilde{\boldsymbol{\phi}}_{\boldsymbol{i}}^{\boldsymbol{j,n}}\right) =& V_{in}\left(\tilde{\boldsymbol{\phi}}_{\boldsymbol{i}}^{\boldsymbol{j,n}}\right) + \epsilon_{in} \\ =& -2\alpha_n \tilde{\tau}_i^j - \beta_{En} SDE\left(h, \hat{t}_n, \tilde{\tau}_i^j\right) - \beta_{Ln} SDL\left(h, \hat{t}_n, \tilde{\tau}_i^j\right) \\ & + I_n - 2\tilde{c}_{in}^j + 2a_{in}^j + \lambda ln\left(\gamma + I_n - 2\tilde{c}_{in}^j + 2a_{in}^j\right) + \epsilon_{in}, \end{aligned} \tag{1}$$

where

$$SDE\left(h, \hat{t}_n, \tilde{\tau}_i^j\right) = \max\left(0, \hat{t}_n - \Delta_a - (t_h + \tilde{\tau}_i^j)\right) \tag{2}$$

$$SDL\left(h, \hat{t}_n, \tilde{\tau}_i^j\right) = \max\left(0, (t_h + \tilde{\tau}_i^j) - \hat{t}_n - \Delta_a\right) \tag{3}$$

$\tilde{\boldsymbol{\phi}}_{\boldsymbol{i}}^{\boldsymbol{j,n}}$ is a vector of forecasted information in the systematic utility that consists of six components. The first is forecasted travel time $\tilde{\tau}_i^j$, which determines the expected schedule delay early (second component) and schedule delay late (third component). The fourth component is expected cost $\tilde{c}_{in}^j$ (operational costs and the toll payment). The fifth component is individual refund in dollars a_{in}^j, if any. The last component is remaining income, which is equal to the disposable income for transportation I_n minus expected cost $\tilde{c}_{in}^j$ plus individual refund in dollars a_{in}^j. ϵ_{in} is assumed to follow an i.i.d. extreme value distribution with zero mean and individual specific scale parameter μ_n. More details on the supply model and the day-to-day learning framework can be found in Chen et al. (2023).

Pricing with no refunding

We denote the instrument of congestion pricing with no revenue refunding as $P-$. The problem of determining the optimal toll in dollars for pricing, $T^{P-}(h)$, $\forall h \in \mathcal{H}$ can be formulated as a simulation-based optimization problem with the objective of maximizing total social welfare (SW) as follows

$$\begin{aligned} \max_{\boldsymbol{T}^{P-}} \quad & Z^{P-} + K^{P-} \\ \text{s.t.} \quad & Z^{P-}, K^{P-} = SM\left(\boldsymbol{T}^{P-}, \boldsymbol{\xi}, \boldsymbol{\psi}\right) \\ & \boldsymbol{T}^{P-} = \{T^{P-}(h) | h \in \mathcal{H}\} \\ & \boldsymbol{T}^{P-} \geq 0 \end{aligned} \tag{4}$$

where ,the toll profile $\boldsymbol{T}^{P-}$ is a set of toll values over the entire day. $\boldsymbol{\xi}$ represents all input data for simulation, such as individual income, preferred arrival time, and choice attributes. $\boldsymbol{\psi}$ represents all model parameters, such as demand model coefficients, bottleneck capacity, user learning weights, and market parameters for the TMC scheme. The $SM(\cdot)$ function is the system model discussed previously. The toll function that we consider is a step toll profile (of the kind implemented in Singapore and Stockholm), which consists of five step toll values and six break points.

The regulator revenue K^{P-} is given by,

$$K^{P-} = \sum_{n=1}^{N} \sum_{i \in M_n \times H_n^{P-}} \hat{c}_{in}^{P-} \mathbb{I}_n \left(i | \boldsymbol{T}^{P-} \right), \tag{5}$$

where i is the mobility decision, $\mathbb{I}_n(i|\boldsymbol{T}^{P-})$ is an indicator if traveler n chooses mobility choice i given toll vector $\boldsymbol{T}^{P-}$; $\hat{c}_{in}^{P-}$ is equal to the toll payment for driving $(T^{P-}(h))$ or the PT fare payment for PT (c_{PT}); and H_n^{P-} is the set of feasible departure time intervals.
We measure user benefits (Z^j) under instrument j as the sum of all users' net experienced utilities relative to NT denoted as z_n^j, given by,

$$z_n^j = \max_{i \in M_n \times H_n^j} \left(U_{in} \left(\boldsymbol{\phi}_i^{j,n} \right) \right) - \max_{i \in M_n \times H_n^{NT}} \left(U_{in} \left(\boldsymbol{\phi}_i^{NT,n} \right) \right), \tag{6}$$

where $\boldsymbol{\phi}_i^{j,n}$ is a vector of experienced variables under instrument j and $\boldsymbol{\phi}_i^{NT,n}$ is a vector of experienced variables under NT.
Hence, the user benefits Z^j can be written as

$$Z^j = \sum_{n=1}^{N} z_n^j \tag{7}$$

Pricing with uniform refunding

For pricing with uniform distribution (PU), the idea is to distribute regulator revenue equally to all users to improve everyone's benefit and make the pricing scheme more politically acceptable. The toll profile optimization can be formulated similarly to the problem formulated in Equation 4 to incorporate the additional revenue refund constraint as follows (δ denotes the fraction of toll revenue redistributed),

$$\begin{aligned} \max_{\boldsymbol{T}^{PU}} \quad & Z^{PU} + K^{PU} \\ \text{s.t.} \quad & Z^{PU}, K^{PU}, E^{PU} = SM \left(\boldsymbol{T}^{PU}, a^{PU}, \boldsymbol{\xi}, \boldsymbol{\psi} \right) \\ & a^{PU} = \frac{1}{N} \delta E^{PU} \\ & \boldsymbol{T}^{PU} = \{ T^{PU}(h) | h \in \mathcal{H} \} \\ & \boldsymbol{T}^{PU} \geq 0 \end{aligned} \tag{8}$$

Under pricing with uniform distribution (PU), the surplus of regulator can be written as,

$$K^{PU} = \sum_{n=1}^{N} \left(\sum_{i \in M_n \times H_n^{PU}} \hat{c}_{in}^{PU} \mathbb{I}_n (i | \boldsymbol{T}^{PU}, a^{PU}) - a^{PU} \right) \tag{9}$$

Pricing with personalized refunding

The pricing with personalized distribution (PI) is formulated as a bi-level optimization problem. The system optimization is to determine the tolling rates with the objective to maximize social welfare and the user optimization is to determine the individual refund under suitable objectives (e.g achieve Pareto improvement or maximize social welfare). These two levels are interdependent in that the system optimization depends on the user optimization solution while the user optimization is also dependent on the system optimization solution. The proposed bi-level optimization framework reconciles often conflicting user and system objectives.
For the system optimization, its objective is the same as the objective of PU, which can be formulated as follows,

$$
\begin{aligned}
\max_{\boldsymbol{T}^{PI}} \quad & Z^{PI} + K^{PI} \\
\text{s.t.} \quad & Z^{PI}, K^{PI}, E^{PI} = SM\left(\boldsymbol{T}^{PI}, \boldsymbol{a}^{PI}, \boldsymbol{\xi}, \boldsymbol{\psi}\right) \\
& \boldsymbol{a}^{PI} = UO\left(\boldsymbol{T}^{PI}(h) | \boldsymbol{\xi}, \boldsymbol{\psi}\right) \\
& \sum_{n=1}^{N} a_n^{PI} \leq \delta E^{PI} \\
& \boldsymbol{T}^{PI} = \{T^{PI}(h) | h \in \mathcal{H}\} \\
& \boldsymbol{T}^{PI} \geq 0
\end{aligned} \tag{10}
$$

where $\boldsymbol{a}^{PI}$ represents a set of refunds over the population $\{a_n^{PI} | n = 1, ..., N\}$ determined from the user optimization (UO) given toll policy $\boldsymbol{T}^{PI}$ determined in system optimization. The total revenue refund has to be less or equal to available revenue for distribution.

The (net) regulator revenue K^{PI} can be written as

$$
K^{PI} = \sum_{n=1}^{N} \left(\sum_{i \in M_n \times H_n^{PI}} \hat{c}_{in}^{PI} \mathbb{I}_n \left(i | \boldsymbol{T}^{PI}, a_n^{PI} \right) - a_n^{PI} \right) \tag{11}
$$

The user optimization (UO) can be formulated in different ways. In order to ensure a Pareto improving outcome (i.e. everyone is not worse off but at least one is better off) compared to NT, the revenue can be distributed to make sure every traveler's net experienced utility relative to NT is non-negative. The personalized refunds with this distribution rule is denoted as PI_H.

Let $z_n\left(I_n - c_{in}^{PI_H} + a_n^{PI_H}\right)$ denote individual n's net experienced utility under PI_H relative to NT as a function of her remaining income $I_n - c_{in}^{PI_H} + a_n^{PI_H}$. The Pareto improving distribution rule can be written as follows,

$$
\begin{aligned}
& \textbf{if} \quad z_n\left(I_n - c_{in}^{PI_H}\right) \geq 0, \quad \textbf{then} \quad a_n^{PI_H} = 0 \\
& \textbf{else} \quad \textbf{set} \quad a_n^{PI_H} \quad s.t. \quad z_n\left(I_n - c_{in}^{PI_H} + a_n^{PI_H}\right) = 0 \\
& \textbf{where} \\
& \quad z_n\left(I_n - c_{in}^{PI_H}\right) = \max_{i \in M_n \times H_n^{PI_H}} \left(U_{in}\left(\boldsymbol{\phi}_i^{PI_H, n}\right)\right) - \max_{i \in M_n \times H_n^{NT}} \left(U_{in}\left(\boldsymbol{\phi}_i^{NT, n}\right)\right)
\end{aligned} \tag{12}
$$

If the individual net experienced utility is already positive, then she receives no refund; otherwise, she receives the amount of refund that makes her net utility equal to 0. Since the income effect is modeled by a strictly monotonic quasi-concave function, which is continuous over the interval that $I_n - c_{in}^{PI_H} + a_n^{PI_H} > 0$, Equation 12 has a unique solution $a_n^{PI_H}$. Note that the condition $I_n - c_{in}^{PI_H} + a_n^{PI_H} > 0$ is guaranteed because of budget constraints.

Alternatively, the objective of user optimization can be to maximize social welfare, i.e. to refund revenue to users who value it the most. In other words, low income users receive revenue refunds first, which implicitly also improves equity. The personalized refunds with this distribution rule is denoted as PI_S. In this case, an additional decision variable that needs to be optimized in the system optimization is the revenue distribution control parameter y_d, which determines who is eligible and how much they can get. Let PI_S denote the instrument with the distribution rule based on the remaining income. The corresponding distribution rule can be written as,

$$
\begin{aligned}
& \textbf{if} \quad I_n - \bar{c}_{in}^{PI_S} \geq \hat{y}_d, \quad \textbf{then} \quad a_n^{PI_S} = 0 \\
& \textbf{else} \quad \textbf{set} \quad a_n^{PI_S} \quad s.t. \quad I_n - \bar{c}_{in}^{PI_S} + a_n^{PI_S} = \hat{y}_d
\end{aligned} \tag{13}
$$

where $\bar{c}_{in}^{PI_S}$ represents the cost of the chosen alternative in PI_S; the revenue distribution control parameter $\hat{y}_d$ is in unit of dollars and can be optimized in the system optimization. This distribution rule also has an unique solution for everyone because the remaining income $I_n - \bar{c}_{in}^{PI_S}$ is a strictly monotonic and continuous function.

Finally, it is possible to combine the Pareto improving distribution rule in Equation 12 and the social welfare maximization distribution rule in Equation 13 to have a hybrid distribution rule, which ensures Pareto improvement first and if there is some revenue left over, it can be distributed to maximize social welfare. As a result, the performance of this hybrid rule can be expected to dominate the pure Pareto improving distribution rule in terms of both efficiency and equity.

The approaches and formulation can be extended to the TMC case although the day-to-day system is more complex due to token price dynamics. We propose a simple approach to compute optimal solutions for the MU and MI instruments as follows. Assume the equilibrium token price is $1, then the system optimization solution —toll profile in dollars, can be converted to toll profile in tokens for MI; while the user optimization solution —personalized refunds in dollars, can be converted to the personalized token allocations.

3 Results and discussion

We adopt the same experimental setup as in Chen et al. (2023). Key model parameters and inputs are summarized in Table 1. The individual daily disposable income I_n is derived from pre-tax annual income, which is a lognormal distribution fitted using the Integrated Public Use Microdata Series (IPUMS) 2019 census data (Ruggles et al., 2021). Individual values of time α_n are calculated as one thirds of the wage rate (White, 2016) and will be varied with different levels of heterogeneity in experiments. The ratio of values of schedule delay early β_{En} to values of time α_n is assumed to follow a triangular distribution from 0.1 to 1 with a mode at 0.5. The ratio of values of schedule delay late β_{Ln} to α_n is assumed to follow a triangular distribution from 1 to 3 with a mode at 2 (Small, 2012).

Table 1: Model and simulation parameters

Variables	**Description**	**Values**
N	Population	$7,500$
Δ_t	Duration of a simulation time step	1 min
Δ_h	Duration of a departure time interval	5 min
Δ_a	Size of desired arrival window	0 min
η	Departure time window size parameter	30
λ	Coefficient of nonlinear income effect	3
γ	Nonlinear income effect adjustment parameter	2
s	Bottleneck capacity (per min)	39
t_0	Free flow travel time	24 mins
c_f	Operation cost of car	$3.13
τ_{PT}	PT travel time	43 mins
W_{PT}	Expected waiting time	5 mins
c_{PT}	Operation cost of PT	$2

Three important factors: capacity, income effect and heterogeneity are varied one at a time across three levels as presented in Table 2. Values used in the base case are highlighted in red.

Table 2: Factor levels for experiments

Factor	Level 1	Level 2	Level 3
Capacity (s)	-15%	0%	15%
Income Effect (λ)	0	3	6
Heterogeneity (c.o.v)	0.2	0.9	1.6

For each scenario, six instruments and NT are simulated with five different random seeds until convergence. The selected instruments are pricing without distribution ($P-$), pricing with uniform distribution (PU), pricing with personalized social welfare maximization distribution rule (PI_S), pricing with personalized hybrid distribution rule (PI_H), TMC with uniform (MU) and personalized distribution (MI) (hybrid rule). For all instruments, the associated bi-level optimization problem is solved using a Differential Evolution (DE) algorithm to determine the optimal toll rates, refunds and credit allocation, and system performance. We assume all regulator revenue is available for redistribution (i.e. $\delta = 1$).
We now discuss findings. First, the premise of achieving Pareto improvement from toll revenue redistribution is that available revenue for distribution can cover total user losses. We find that this

holds for the pricing without distribution instrument $P-$ across all of our simulation experiments as shown in Figure 2, where Z_L represents the aggregate user losses and K represents the regulator revenue.

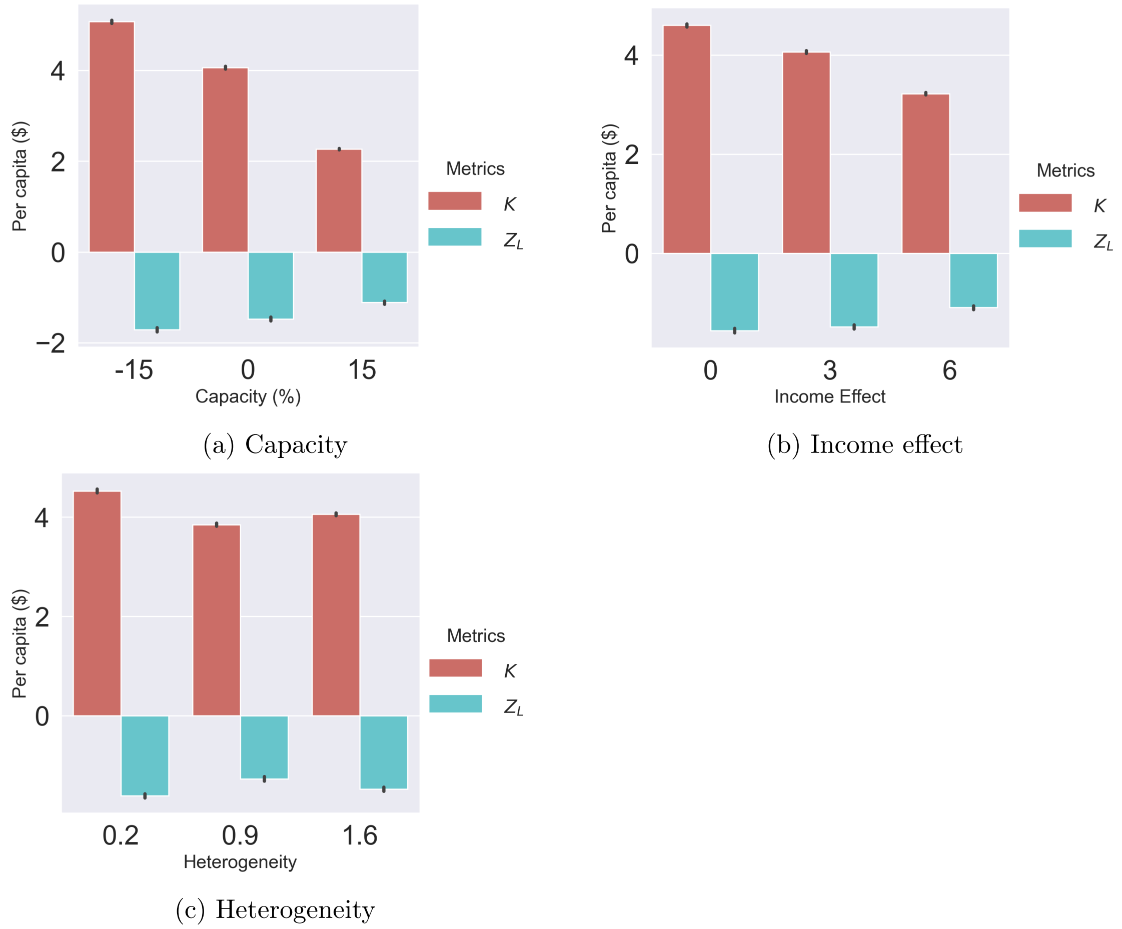


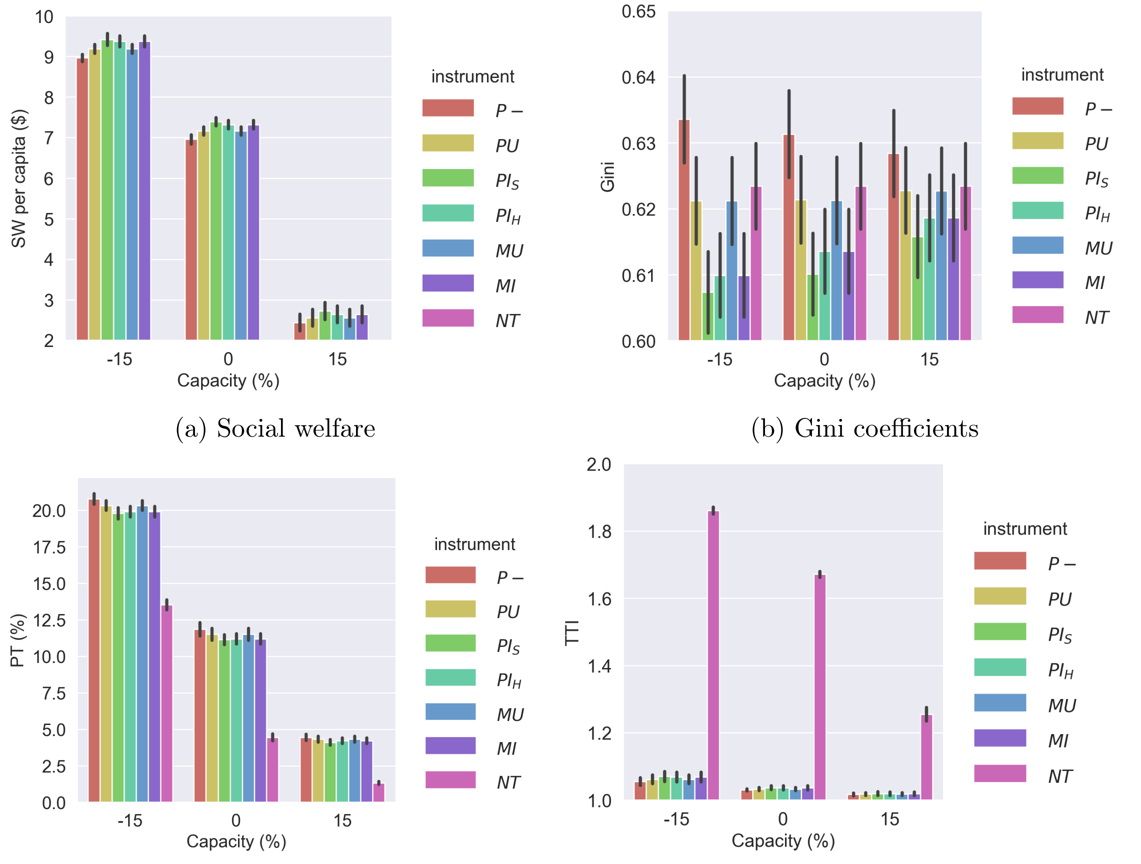
Figure 2: Regulator revenue versus user loss for the pricing without distribution ($P-$)

The comparative performance of the various instruments under varying levels of capacity (for brevity we focus only on capacity) in terms of social welfare, Gini coefficient (GC), PT share and travel time index (TTI) are shown in Figure 3. The social welfare is computed relative to the NT and consists of the user benefit and regulator revenue.

As capacity level decreases, congestion increases and the social welfare of all instruments increase relative to NT. Among all instruments, PI_S achieves the highest social welfare as its distribution rule is to maximize social welfare directly. The pricing with hybrid distribution rule PI_H has social welfare less than that of PI_S as its revenue is distributed to compensate all users' losses (not only low-income users) to ensure Pareto improvement. The pricing with uniform distribution PU has social welfare less than that of PI_H as its revenue is distributed uniformly to all users including those who do not have losses.

We can also observe than TMC with uniform token allocation MU performs the same as PU and TMC with personalized token allocation MI performs the same as PI given the effect of transaction fees are minimal. This is because the market value of token allocation is roughly equal to the dollar value of the corresponding refund, which causes similar behavior changes since the income effects are similar.

GC is calculated using the individual disposable income I_n plus her benefit z_n. GC of $P-$ increases as capacity level decreases, which implies that $P-$ becomes less equitable. This is because as capacity level decreases, the toll has to increase to deal with the increasing congestion leading to the greater losses of low income users. Among all instruments, PI_S is the most equitable because the social welfare maximization distribution rule also directly benefits low income users. It becomes more equitable as capacity level decreases because more revenue can be distributed to benefit low income users. PI_H is less equitable than PI_S because its revenue is distributed to compensate all users' losses. PU is less equitable than PI_H because its revenue is distributed uniformly to all users. The TMC instruments have the same equity as the corresponding pricing instruments with



(a) Social welfare

(b) Gini coefficients

(c) PT share

(d) Travel Time Index

Figure 3: Variation of performance measures with capacity

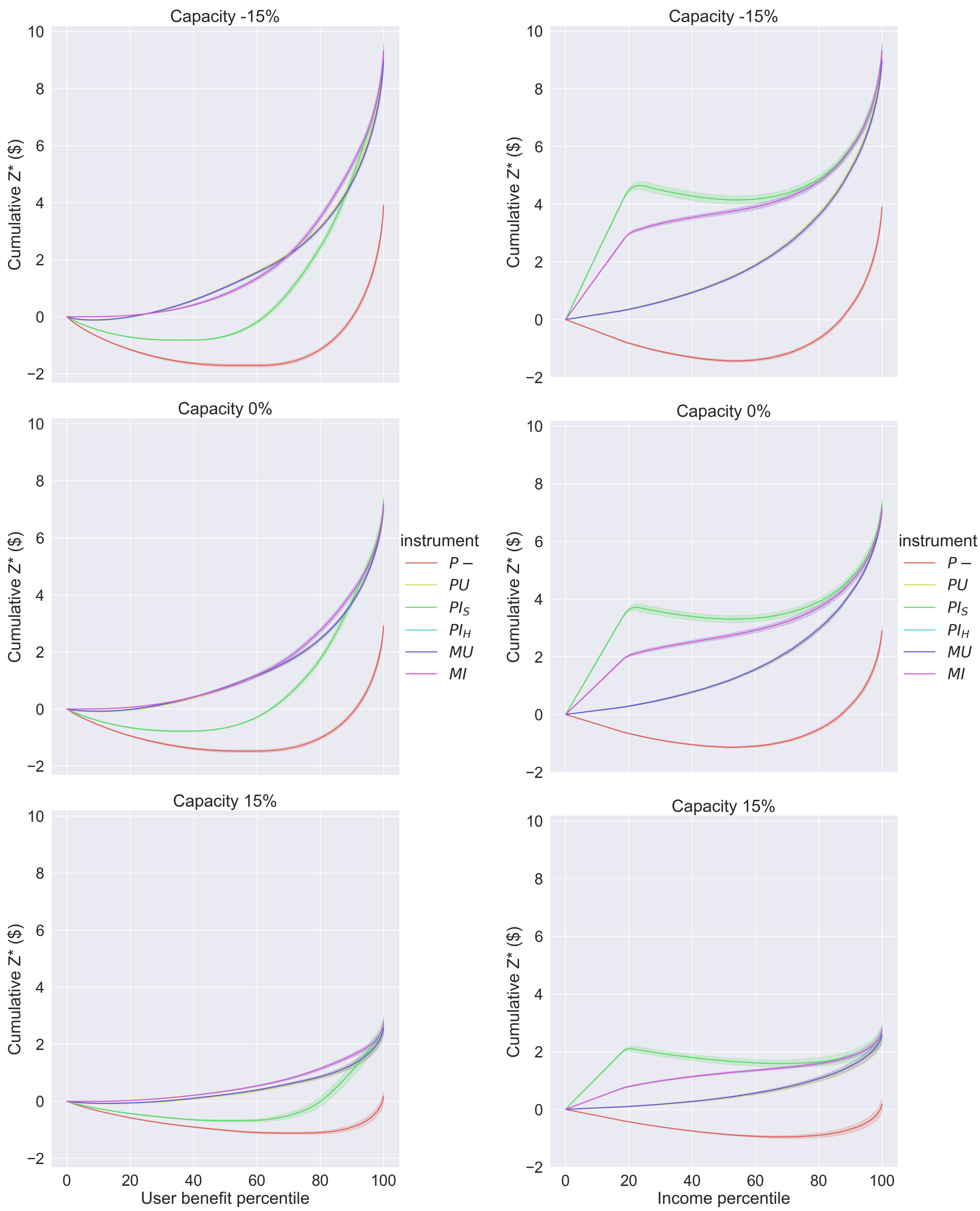
refunding because of similar reasons mentioned in social welfare discussion. A uniform refund or token allocation always improves the Gini coefficient because it increases the proportion of user benefits obtained by the lower income segments.

The distributional impacts of instruments are shown in Figure 4. The y-axis is cumulative user benefits normalized by population size. The x-axis of Figure 4a (left column) is user benefit percentile while the x-axis 4b (right column) is income percentile. If an instrument is Pareto improving, then its line should not go below 0 in Figure 4a. In addition, if an instrument is progressive, then its line will increase fast initially in Figure 4b, which means low income users have a large share of user benefits.

We can observe that $P-$ is regressive and not Pareto improving because low income users have losses in Figure 4a. Uniform distribution (PU and MU) cannot eliminate "losers" because every user receives the same amount of refund. Although PI_S benefits low income users significantly compared to other instruments as shown in Figure 4b, the mid income users still have losses. PI_H and MI are not only progressive in that they benefit low income users more than other users as shown in Figure 4b, but also Pareto improving since no user has a loss as shown in Figure 4a.

4 Conclusions

The results demonstrate that the developed bi-level optimization framework can significantly improve the distributional impacts of congestion pricing to achieve progressive Pareto improving outcomes while attaining comparable welfare gains and congestion reductions as pricing with refunding. This is promising and could improve the public acceptance of congestion tolling as it addresses the important and long-standing issue of equity.



(a) Ordered by benefit (Lorenz curve)

(b) Ordered by income

Figure 4: Variation of cumulative user benefits with capacity

References

Arnott, R., De Palma, A., & Lindsey, R. (1994). The welfare effects of congestion tolls with heterogeneous commuters. *Journal of Transport Economics and Policy*, 139–161.

Azevedo, C. L., Seshadri, R., Gao, S., Atasoy, B., Akkinepally, A. P., Christofa, E., … Ben-Akiva, M. (2018). Tripod: sustainable travel incentives with prediction, optimization, and personalization. In *Proceedings of the transportation research record 97th annual meeting.*

Chen, S., Seshadri, R., Azevedo, C. L., Akkinepally, A. P., Liu, R., Araldo, A., … Ben-Akiva, M. E. (2023). Market design for tradable mobility credits. *Transportation Research Part C: Emerging Technologies*, *151*, 104121.

de Palma, A., & Lindsey, R. (2011). Traffic congestion pricing methodologies and technologies. *Transportation Research Part C: Emerging Technologies*, *19*(6), 1377–1399.

Grant-Muller, S., & Xu, M. (2014). The role of tradable credit schemes in road traffic congestion management. *Transport Reviews*, *34*(2), 128–149.

Gu, Z., Liu, Z., Cheng, Q., & Saberi, M. (2018). Congestion pricing practices and public acceptance: A review of evidence. *Case Studies on Transport Policy*, *6*(1), 94–101.

Guo, X., & Yang, H. (2010). Pareto-improving congestion pricing and revenue refunding with multiple user classes. *Transportation Research Part B: Methodological*, *44*(8-9), 972–982.

Jaensirisak, S., May, A. D., & Wardman, M. (2003). Acceptability of road user charging: the influence of selfish and social perspectives. In *Acceptability of transport pricing strategies.* Emerald Group Publishing Limited.

Lindsey, R., & Verhoef, E. (2001). *Traffic congestion and congestion pricing.* Emerald Group Publishing Limited.

Liu, W., & Szeto, W. Y. (2020). Learning and managing stochastic network traffic dynamics with an aggregate traffic representation. *Transportation Research Part B: Methodological*, *137*, 19–46.

Nie, Y. M., & Liu, Y. (2010). Existence of self-financing and pareto-improving congestion pricing: Impact of value of time distribution. *Transportation Research Part A: Policy and Practice*, *44*(1), 39–51.

Ruggles, S., Flood, S., Foster, S., Goeken, R., Pacas, J., Schouweiler, M., & Sobek, M. (2021). *Ipums usa: Version 11.0.* (Minneapolis, MN: IPUMS, 2021. https://doi.org/10.18128/D010.V11.0)

Small, K. A. (1992). Using the revenues from congestion pricing. *Transportation*, *19*(4), 359–381.

Small, K. A. (2012). Valuation of travel time. *Economics of transportation*, *1*(1-2), 2–14.

White, V. (2016). Revised departmental guidance on valuation of travel time in economic analysis. *Office of the Secretary of Transportation, US Department of Transportation, Available at: transportation. gov/sites/dot. gov/files/docs/2016% 20Revised% 20Value% 20of% 20Travel% 20Time% 20Guidance. pdf*.

Wittman, M. D., & Belobaba, P. P. (2017). Personalization in airline revenue management–heuristics for real-time adjustment of availability and fares. *Journal of Revenue and Pricing Management*, *16*(4), 376–396.

Xiao, F., & Zhang, H. (2014). Pareto-improving toll and subsidy scheme on transportation networks. *European Journal of Transport and Infrastructure Research*, *14*(1).

Xie, Y., Zhang, Y., Akkinepally, A. P., & Ben-Akiva, M. (2020). Personalized choice model for managed lane travel behavior. *Transportation research record*, *2674*(7), 442–455.

Zhang, Y. (2019). *Real-time personalized toll optimization based on traffic predictions* (Unpublished doctoral dissertation). Massachusetts Institute of Technology.