Assessing the health impact of proposed congestion pricing plan for downtown San Francisco

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16. Abstract
Congestion pricing (CP) is seen as a viable solution to urban traffic congestion, but its impact on public health also deserves to be evaluated before implementation. In this study, we assessed several congestion pricing schemes proposed for the San Francisco downtown area from a health perspective. We compare the eight proposed CP schemes with baseline scenario (no-action) to observe the health effects from physical activity (PA), fine inhalable particles matter (PM) exposure, and road traffic injuries (RTI) three pathways using the Integrated Transport and Health Impact Model (ITHIM). The results of the study show that these CP schemes all have a beneficial effect on the public health of San Francisco. Finally, we recommend further research on TNC travel fees in these CP schemes and explore the potential for health improvements on physical activity by encouraging people to use active modes of transport.

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Introduction

Traffic congestion is a growing problem that costs hundreds of billions of dollars in terms of fuel and delays in large urban areas (Ellis & Glover, 2019). The downtown San Francisco neighborhoods, as a large metropolitan area, are also experiencing a serious traffic congestion problem. In this area, from 2009 to 2017, the average travel speeds in afternoon peak hours decreased from 16.7 mph to 12.2 mph on arterial, 31.3 mph to 26.4 mph on freeways, and vehicle hours of delay have increased by 63% (Castiglione, et al., 2019). This change resulted in delays in traffic, the less reliable arrival time for buses, greater risk of injury to non-motorized transport, and adverse effects on public health, especially low-income communities more likely to live in congested areas.

Many cities around the world implemented Congestion Pricing (CP) strategies to mitigate congestion effects, such as Gothenburg (Swedish Transport Agency (Transportstyrelsen), 2021), London (Transport for London, 2021), Singapore (Singapore Land Transport & Authority, 2021), Stockholm (Swedish Transport Agency (Transportstyrelsen), 2021), and Vancouver (City of Vancouver, 2020). To address traffic congestion and meanwhile mitigate the associated negative impacts on the environment, health, and transportation equity, San Francisco County Transportation Authority (SFCTA) also intends to apply CP strategies for the downtown San Francisco area (San Francisco County Transportation Authority, 2019). In the last paper (Kanglong, Zenghao, & Michael, 2021), we applied a modified Gini index to measure equity in two dimensions: travel time and travel cost and compare the effects of different pricing schemes on transportation equity. However, the determinants of transportation policies can also harm health and create inequality across all communities (San Francisco County Transportation Authority, 2019), which was not included in the previous study.

Although there are few existing studies on the health of congestion pricing, researchers have tried to assess it from different perspectives. One is in terms of air quality, as congestion relief reduces vehicle emissions, which in turn helps improve air quality. In London, the air quality improvement inside the charging zone was estimated to be 7–8 % in oxides of nitrogen (NO_x) and particulate matter with diameters that are generally 10 micrometers and smaller (PM_{10}) (Transport for London, 2008). A study in Stockholm (Simeonova, Currie, Nilsson, & Walker, 2021) showed that the NO_2 and PM_{10} levels in the congestion pricing zone fell by around 15%. The congestion pricing plan will result in a 16% drop in acute asthma hospital visits of children who live inside the zone in a trial scope and a 50% drop in the permanent implementation scope. Another assessment, or say an intuitive inference, is that congestion pricing will encourage people to use healthier modes of travel and increase their physical activity. (Brown, Moodie, & Carter, 2015) pointed out that the evidence is still limited, at least from the congestion pricing project in Stockholm (Eliasson, 2009). Our study also modeled the physical activities aspect and estimated that the health gains obtained are indeed smaller compared to the other aspects. Last, congestion pricing also contributes to improvement under other aspects, such as traffic injuries reduction, and financial

savings. (Transport for London, 2008) stated that the congestion pricing implementation led to a 40--70 reduction in the number of traffic injuries per year. Two congestion pricing plans in New York City were analyzed (Yu, et al., 2019) and estimated to bring $24,000 per capita in form of economic savings. Based on their assumption between Quality Adjusted Life Year (QALY) and the willingness to pay, they also assessed a 0.10 QALY improvement per capita from a rather economic perspective. To summarize, some of these studies focused on only one aspect of transportation health, while others failed to summarize all aspects into a single outcome value. Unlike the above health studies on congestion charging, this study will quantify health impacts in terms of resident movement, air quality, and traffic accidents, and aggregate the results into a single scalar value.

In this study, we focus on the health assessment of the CP schemes and discussion of the impact of congestion pricing schemes on public health. We use Disability Adjusted Life Years (DALYs) as the metric of health condition and apply Integrated Transport and Health Impact Modelling (ITHIM) (Woodcock, et al., 2009) to quantify the net health impact from Physical Activity (PA), hazardous air exposure (mainly PM 2.5 (USAID & CCAD, 2012)), and Roadway Traffic Injuries (RTI) three Pathways. Given eight proposed CP schemes and SF-CHAMP model outputs, we set these eight outputs as alternative scenarios and exiting conditions (no-action) as the baseline scenario. By comparing the baseline scenario with each proposed alternative scenario, we could understand the changes of DALYs and further evaluate the health impact of each alternative. Finally, we rank these proposed schemes and provide conclusions and guidance to future congestion policymakers on scheme adjustments or other supporting measures to further improve public health.

Project Background

The congestion pricing region for this study is the Northeast Cordon of San Francisco (Figure 1), which is defined on the west by Laguna Street and the south by 18th Street. Considering the impact of various factors such as price level, discount for certain groups, and travel directions, SFCTA proposed eight pricing alternatives and they are labeled alphabetically from A to H (see Table 1).
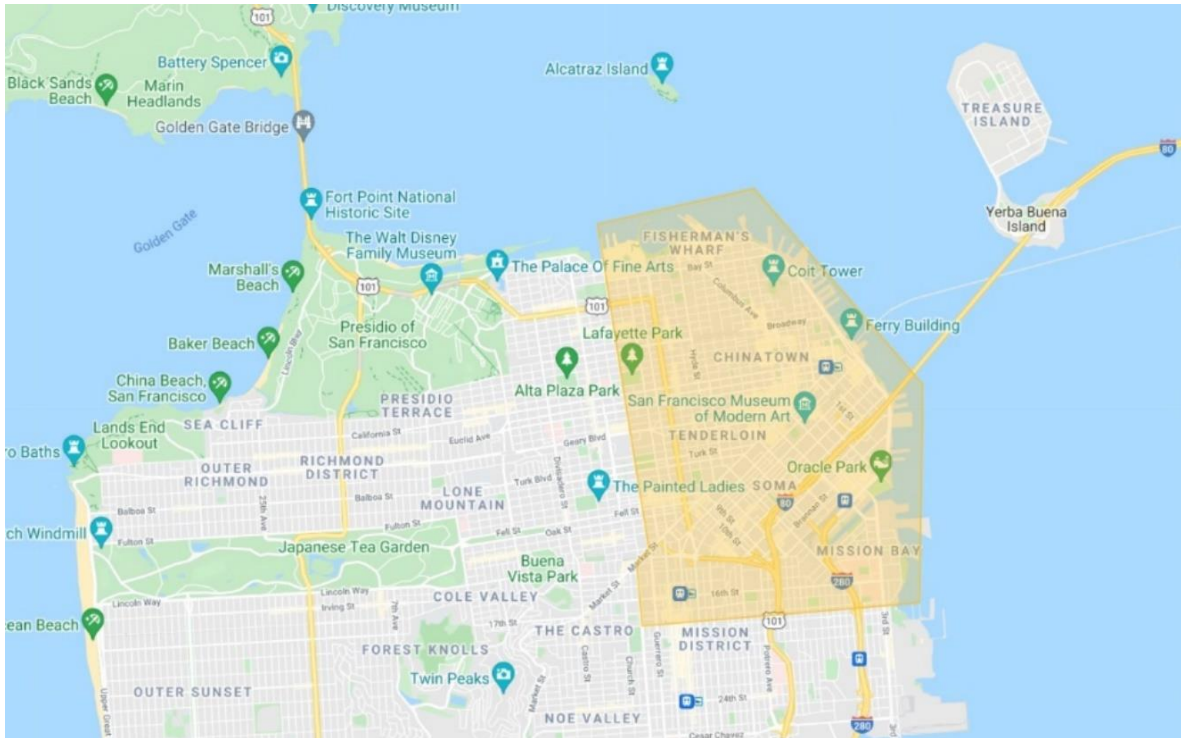
Figure 1 An Illustration of the Proposed Congestion Pricing Area (Highlighted on the Map) in San Francisco. (Source: Google Map)

Table 1 Description for the Proposed Congestion Pricing Schemes

Scenarios	Charge Type	Price	Discount for Income Groups			Discount for Resident	Other Fees/Tolls
			Very Low	Low	Moderate		
A	Bidirectional	$5.50	100%	50%	0%	0%	/
B	Inbound	$8.50	0%	0%	0%	0%	/
C	Inbound	$10.00	50%	50%	0%	0%	/
D	Inbound	$10.50	100%	50%	0%	0%	$10.50 TNC trip fee
E	Inbound	$12.00	100%	50%	0%	0%	/
F	Inbound	$12.50	100%	67%	33%	0%	$12.50 TNC trip fee
G	Inbound	$12.50	100%	50%	0%	50%	/
H	Inbound	$14.00	100%	50%	0%	50%	$1.75 bridge toll

Here are some notes for understanding the scheme details in Table 1:

- Bidirectional policies: refer to those that charge trips either entering or exiting designated pricing areas.

- Inbound policies: only charge when travelers enter the congestion pricing area.

- Discount: offers monetary supplements to Very Low, Low, and Moderate income groups (categorized by Area Median Income) and residents.

- Extra charging: charge additional fees for special trips, such as TNC trip fees and bridge toll.

SFCTA used SF-CHAMP model (San Francisco County Transportation Authority) to predict the traveler's mode choice, network congestion level, and estimate vehicle emissions. The output data consist of household or personal data (including income, age, and gender) and trip data (including the origin and destination (OD), start and end time of the trip, the travel mode used, and the travel cost).

Methodology

The basis of ITHIM is the Comparative Risk Assessment (CRA) method, a method for measuring changes in disease burden (DB) from baseline to changes in exposure factors in other scenarios (Kay, Prüss, Corvalán, & others, 2000). These exposure factors include physical activities (PA) and the concentration of inhalable hazardous particulate matter (PM). We set the baseline scenario as the exiting (no-action) condition in 2015 for the San Francisco urban area. The alternatives are described in the previous section. Furthermore, PA, PM, and road traffic injuries (RTI) are recognized as the main factors to the impacts of public health (Mindell, Rutter, & Watkins, 2011), and our study also builds on these three pathways. We observe the change factor in DB that result from the shift between a baseline scenario to an alternative scenario, expressed by:

$$R = \frac{\int RR(x)P_H(x) - \int RR(x)P_B(x)}{\int RR(x)P_B(x)}, \tag{1}$$

where subscript B represents the baseline scenario and subscript H represents a hypothetical scenario, so P_B and P_H is the population distributions over age groups to exposure level x in baseline and hypothetical scenarios, respectively. For example, for the PA pathway, the exposure is measured by the MET-hours of all physical activities.

We use Disability-Adjusted Life Years (DALYs) as the metric to measure the impact of BD on human health. The DALYs information was obtained from the Global Burden of Disease (GBD) database for the U.S. in 2015. However, it is difficult to find the associated BD information for the SF area, we used the whole California GBD data instead (Global Burden of Disease, 2015). By collecting The SF population census data (NHCRP, 2015) and California census data (NHCRP,

2015), we scaled down the number by using the ratio of the population of California state to that of the SF urban area.

We quantified the physical activity as the sum of travel activity and non-travel activity in the unit of metabolic-equivalent task (MET) hours. Travel activity is the amount of activity generated when using an active mode of transportation in a transportation trip. We refer to the active transport information from the SF-CHAMP model, such as walking speed (3mph) and cycling speed (6mph). For the non-travel activity information, we refer to the model settings from another SF bay area health study of the United States: a bay area health study (Maizlish, et al., 2013) for non-travel activity estimation.

To estimate the impact of air pollution on public health, we consider PM2.5 as the main factor of exposure and used the concentration of PM2.5 for the evaluation. We used the predicted travel data and historical VMT data (Bay Area Metro, 2018) to obtain the decreasing values of VMT and a linear regression model built on PM2.5 data (United States Environmental Protection Agency, 2015) between 2005 and 2015 to predict the change of PM2.5. VMT changes are estimated from the change of the baseline and schemes trip data adjusted by the population ratio.

From physical activity and air pollution aspects, the impact on the health of the general public is quantified by the risk of different diseases. The causes impacted by physical activity include diabetes, dementia, depression, colon cancer, cardiovascular diseases, and breast cancer. Similarly, those impacted by air pollution include lung cancer, respiratory diseases and infections, and cardiovascular diseases.

ITHIM models the RTI through injuries or fatalities of on-roads, single- and multi-party traffic collisions from both strike and victim sides. By assuming the accident rate of each strike-victim type is unchanged across both scenarios, the change factor R can be expressed as:

$$R_{RTI} = 1 - \left[\frac{L_H^u L_H^v}{L_B^u L_B^v} \right]^{\frac{1}{2}}, \tag{2}$$

where L^k is the total miles traveled of mode k, which includes walking, biking, and driving. Subscripts B and H represents the results under baseline and hypothetical scenario. The collision data was derived from a database (Transbase, 2015), which data is being provided by the San Francisco Department of Public Health (SFDPH), the San Francisco Municipal Transportation Agency (SFMTA), and the San Francisco Police Department (SFPD). We filtered the data to keep the records for 2015 only.

Finally, we multiply the DALY values of the baseline scenario by the change factor to obtain the change in health brought by the current congestion charging scheme compared to the baseline. Since we subtract the value of the baseline from the value of the current scenario (Equation 1)111,

a negative number indicates that the CP scheme reduces disease burden, or say it brings health benefits.

Results

We find that all the alternatives provide health benefits to the SF urban area. Scenario A to H generate -29.4, -18.1, -15.8, -2.9, -25.0, -5.0, -17.0, - 17.0 DALYs for the population in SF urban area annually, respectively (Figure 2 and Table 2). Negative values in a congestion pricing scenario mean the public health is improved over the baseline scenario. Most of the DALY items are negative, indicating that congestion pricing is beneficial to public health in all the three PA, PM, and RTI pathways. In Scenarios D and F, RTI health impacts are negative for reasons we will discuss in the following section.

Table 2 Health Impact Results Measured in Disability Adjusted Life Years (DALYs) of Each Scenario in PA, PM, and RTI Pathways

DALYs	A	B	C	D	E	F	G	H
Physical Activity	-0.019	-0.020	-0.022	-0.019	-0.016	-0.018	-0.019	-0.023
Particle Matters	-12.544	-10.759	-10.190	-7.111	-12.284	-7.415	-10.953	-11.595
Road Traffic Injuries	-16.836	-7.309	-5.564	4.232	-12.700	2.434	-6.035	-5.334
Total	-29.399	-18.088	-15.777	-2.897	-25.000	-4.999	-17.007	-16.952
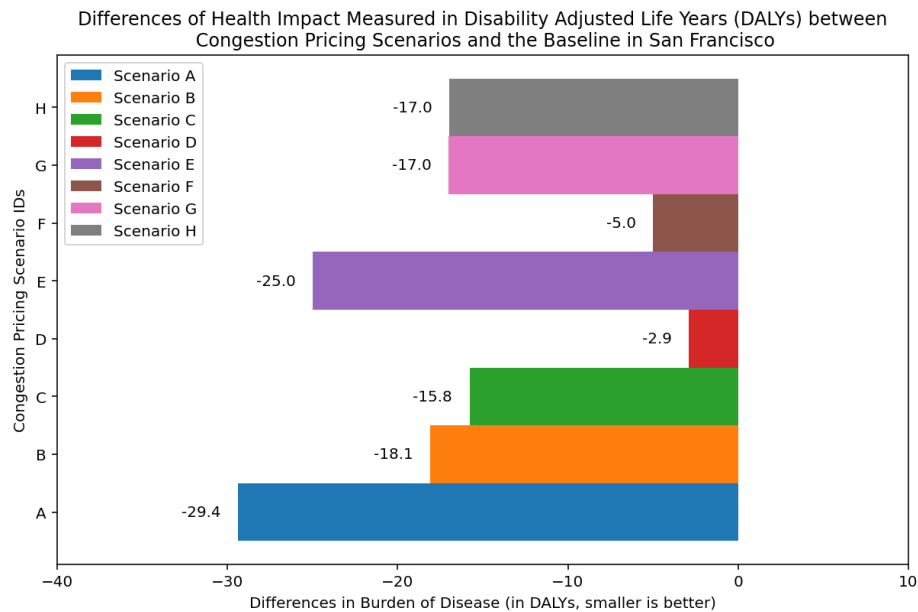
Figure 2 DALYs changes between baseline and alternative scenarios

Conclusions and Discussions

To conclude, our study shows that the implementation of any congestion pricing strategy will result in public health benefits. These schemes will reduce VMT, improve PM 2.5, and thus lead to beneficial health impacts in the PM and RTI pathways. The amount of physical activity in the congestion pricing schemes is maintained at almost the same level, compared with the baseline (without congestion pricing). Among all the congestion pricing schemes, scenarios A and E perform better than other schemes in terms of DALYs. This is due to their larger reduction in VMT (around 59000 vehicle-miles), resulting in a greater decrease in the number of predicted traffic accidents.

Nonetheless, we need to point out that such benefits may be relatively small. Since tolls are limited to peak hours and the toll zone, it is understandable that the benefits of these tolling schemes to public health are somewhat limited. Congestion pricing will reduce VMT and help reduce PM2.5 concentrations, and these two pathways are where its core impact lies. However, we find that for PA aspect, congestion charging brings almost no impact. We speculated that the congestion charge would induce many travelers to switch to active modes of travel, but the health benefits of this change remain relatively small in light of the results of the PA predictions. In this regard, congestion pricing still has the potential to further improve public health. Together with policies or subsidies that encourage people to use active travel modes, we can expect to make attract more people to change their travel choices and thus bring about greater public health benefits.

Although the health assessment results are relatively close across congestion charging policies, there are still some interesting points to explore. We note that the two schemes with the least health benefits (D and F) are the only two schemes that apply TNC trip fees. This suggests that charging TNC fees is likely to be detrimental to improving public health. From Table 2, we see that the RTI values for these two scenarios are positive, which means that accidents are expected to increase after the implementation of the scenarios. This is because the increase in the amount of people walking brings an impact on the accident rate even more than that brought by the decrease in VMT. It is an interesting finding that limiting TNC brings longer walks, which increases predicted accidents and thus diminishes the benefit of VMT decline with PM2.5 improvement. This inspires us to perhaps take more modest measures on TNC restrictions (e.g., lowering the TNC trip fee in these congestion pricing schemes) and that further research should be conducted on the health effects of TNC restrictions.

We have the following suggestions for future work. First, since the health benefits in the results of this study are relatively small for the entire San Francisco area, we suggest narrowing the study area. Many existing health studies of congestion pricing are specific to the pricing zone only, which allows people to have a closer look and understand the impact of congestion pricing more easily. Of course, this would also need to be supported by more granular regional data (e.g., street-level air quality monitoring stations, medical data from the toll zone, etc.). Second, as stated above,

more TNC cost comparison scenarios should be set up to further study the impact it has on public health. Due to the limitations of the scenarios, we are not able to draw exact conclusions on how TNC costs affect health in this study, but it is certainly a worthwhile research topic. Finally, try to match congestion pricing with other transportation policies to shift more people towards active travel modes. This would help tap into the impact of congestion pricing in terms of physical activity, leading to greater public health benefits.

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