Who Pays for Congestion? The Incidence of Congestion Tolls on California Highways

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In the United States, costs of traffic congestion exceed $100 billion per year (Schrank and Lomax, 2021). Congestion wastes time, increases fuel consumption, causes environmental damage and creates negative health impacts. To address these concerns, economists favor Pigouvian pricing in the form of congestion tolls. Since traffic conditions vary substantially by location and time of day, congestion tolls will affect drivers differently based on where and when they travel. The potential for distributional effects has been a major concern, creating barriers to adoption of congestion pricing.

This study seeks to answer the following questions:

1.) How do driving patterns vary by individual and household characteristics?
2.) How do congestion costs vary by location, time of day and day of week?
3.) What are the distributional effects of congestion pricing?
4.) How does the incidence vary based on the design of the congestion toll?

Policymakers and the general public have highlighted the potential for congestion charges to disproportionately impact low-income individuals and minority communities who may have limited transportation alternatives or face higher travel costs (Murphy (2017), UCLA (2019), Berger (2008)). However, the existing evidence on the equity of congestion tolling is limited and mixed, with a few small area studies and simulations producing conflicting results, including suggestions that congestion charges could be progressive, regressive, or neutral (Arnott, De Palma, and Lindsey (1994), Santos and Rojey (2004), Schweitzer and Taylor (2008), Krol (2016), Ke and Gkritza (2018)). A priori, the potential incidence of new tolls is unclear. On one hand, well-off households drive more. They are more likely to live outside the city center, far from work, and as a result, are more likely to have a costly commute. On the other hand, less well-off households may have less flexible work arrangements and may be constrained to commutes during peak hours.

To investigate these issues, this study will utilize detailed traffic flow data from thousands of locations in California to investigate the distributional effects of congestion charges. We propose a straightforward technique for estimating time-varying and location-specific

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marginal external congestion costs (MEC). This approach can be applied by policymakers in a variety of settings including those with more limited data than exploited here. We will use these estimated MECs to design Pigouvian and second-best tolls. We will assign tolls to individual trips reported in the National Household Travel Survey to estimate the total cost for each household under the different toll policies. Our analysis will determine whether tolls based on real-time traffic costs or second-best approximations based on location and/or hour, lead to systematically different effects on different populations.

Potential to inform research and policy interests of DOT

Our research offers an approach to measuring the costs and benefits of federal transportation policies by utilizing detailed traffic flow data to estimate marginal external congestion costs (MECs) and the distribution of the costs over a range of demographic dimensions such as affluence, race, and age, as well as geographic location and access to alternative transportation options. This comprehensive approach allows us to inform various toll policies and assess their distributional effects, which enables us to evaluate the impact of transportation policies on disadvantaged communities.

Proposed research design

The proposed project will combine highly detailed data on traffic conditions from the California Freeway Performance Measurement (PeMS) system with individual trip-level data from the National Household Travel survey California Add-On (NHTS-CA). There are three main stages in the analysis:

Stage 1: Estimate marginal external congestion costs

We will estimate marginal external costs (MEC) of traffic congestion using hourly data on traffic speed and flow from the PeMS system. PeMS reports traffic conditions from approximately 40,000 detectors at over 9,300 locations within the state. For each detector, we will estimate the relationship between travel time (T) and vehicle density (n). During uncongested periods, changes in vehicle density (highway use) have no effect on average travel time. However during congested periods, additional vehicles reduce speeds and increase travel times. Figure 1 illustrates these features for a representative location in Los Angeles. The slope of the travel-time density relationship, $\frac{\partial T}{\partial n}$, gives the marginal effect of an additional vehicle on travel time. The marginal external (time) cost is the product of the marginal time effect and the number of highway users: $n\frac{\partial T}{\partial n}$.

To capture these effects empirically for each location we will estimate:

$$T_{it} = \beta_0(n_{it} < c) + [\beta_0 + \beta_1(n_{it} - c) + \beta_2(n_{it} - c)^2] * (n_{it} \geq c) + Weather_{it}\alpha + \epsilon_{it} \qquad (1)$$

where T_{it} is average travel time at location i at time t and n_{it} is vehicle density. In the piecewise relationship, c is the critical vehicle density corresponding to the onset of congestion, β_0 is the uncongested travel time, $(n_{it} < c)$ and $(n_{it} \geq c)$ are indicator functions. $Weather_{it}$ is vector of weather controls that affect driving demand and also the relationships between travel time and vehicle density.[1] Once the travel-time vehicle-density relationships (1) are

[1] As noted by Yang, Purevjav, and Li (2020), estimates of Equation 1 could be biased due to endogeneity.

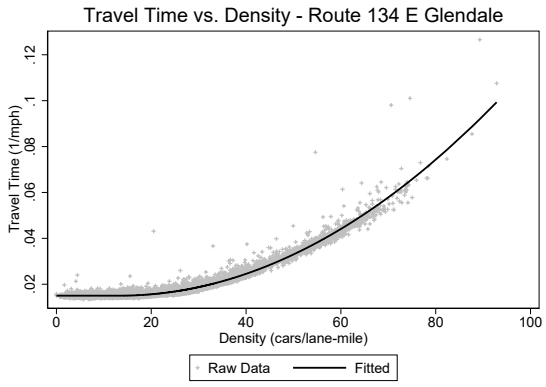


Figure 1: Representative TT-density fit for a monitor in Los Angeles.

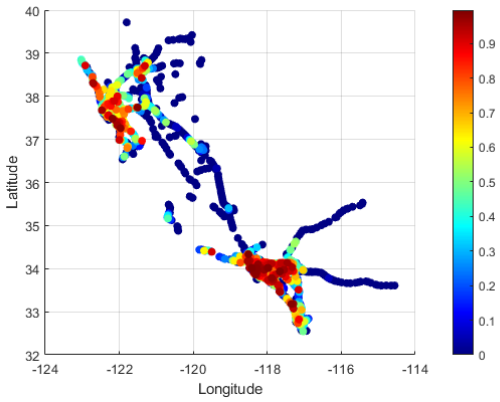


Figure 2: Average MECs ($/car-mile) for each monitor: All CA Districts

estimated, the marginal external congestion costs can be calculated using the observed density at each location during every hour of our sample.[2] Figure 2 summarizes average MEC estimates for locations across California.

Stage 2: Match NHTS household trips to routes

Next, we will match individual trips from the 2017 NHTS-CA to routes on California roadways. The NHTS is a nationally representative survey administered by the Federal Highway Administration (FHWA) that contains daily travel and household demographic data. Through agreement with the National Renewable Energy Laboratory Transportation Secure Data Center, we will utilize the confidential geospatial data in the NHTS-CA for the latitude and longitude of each trip origin and destination. Then, we will assign each trip to the road network using an optimal routing algorithm implemented in OpenStreetMap.

Once trips have been assigned to routes, we can estimate the congestion tolls incurred during each trip under different policy scenarios. Pigouvian tolls are calculated by aggregating the MEC estimates from Equation 1 along each route. We will also estimate tolls under several second-best policies.[3]

Stage 3: Estimate incidence of different tolling policies

The final stage of the analysis will compare toll expenditure across policies along different demographic dimensions, *e.g.* affluence, race and age. To illustrate our approach, we present several sets of results using tolls based on zip code level average MEC's and aggregate household characteristics from the public version of the NHTS. We focus on three potential

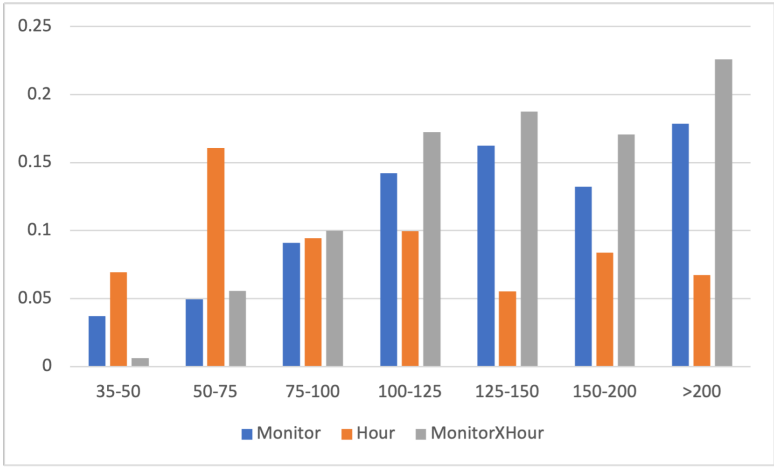
We will address this possibility using an instrumental variables strategy where the shock to travel demand during the early stages of COVID is used to identify the travel time density relationship.

[2]To monetize this cost, we will use average values of travel time from the literature (Small, Winston, and Yan, 2005; Bento, Roth, and Waxman, 2020).

[3]Because measuring actual costs may be expensive or impractical in settings with substantial variability, policymakers may instead set second-best tolls based on average values. For instance, tolls based on monitor average MECs that do not vary with time, average hourly tolls that are the same across locations, and tolls vary by each monitor and hour.

second-best tolling schemes: tolls based on the average MEC at each highway location (monitor); tolls based on the average MEC during the hour of travel; and monitor-specific average hourly MECs. The incidence of these tolling schemes are summarized in Figure 3 for different points on the income distribution.[4]

Figure 3: Percentage Annual Toll Expenditure Increment by Income Level



The preliminary results suggest the policy design is quite important for the ultimate incidence of congestion tolls. Second-best tolls based on spatial difference in MECs, *i.e.* monitor and monitor-by-hour averages, are *progressive*. Households earning $50,000 to $75,000 per year pay, on average, 0.05 percent of their income in congestion tolls. Households earning over $200,000 pay 0.17 to 0.22 percent. However, second-best tolls based only on average congestion during by hour of day appear somewhat *regressive*. Households earning $50,000 to $75,000 per year pay approximately 0.16 percent of their income compared to approximately 0.06 percent for higher earning households. Under all three policies, the lowest earning households pay very little in tolls, presumably because they have few car trips. Preliminary insights from analysis of the aggregate data suggest much more can be learned about the incidence of different tolling policies from the analysis of trip-level data and household characteristics proposed here.

More broadly, policymakers can apply the estimation techniques we develop here to produce realtime, location-specific MEC estimates in their own settings. Once the travel-time vehicle density relationship has been estimated for a given roadway, the MEC can be calculated using only information on vehicle density. Therefore, this approach may further the adoption of congestion tolls in the future.

Conflict of interest

The authors declare that they have no relevant or material financial interests that relate to the research described in this proposal.

[4]Since reported income may be a poor measure of permanent income, subsequent analysis will adopt the approach of Glaeser, Gorback, and Poterba (2023) to estimate household annual expenditures to use as our measure of affluence.

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