Using big data to estimate the environmental benefits of congestion pricing in the Los Angeles Metropolitan Area

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A research report from the Pacific Southwest Region University Transportation Center

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The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

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Disclosure

The Principal Investigator conducted this research titled, "Using Big Data to estimate the environmental benefits of congestion pricing in the Los Angeles Metropolitan Area" at Sol Price School of Public Policy, University of Southern California. The research took place from 04/01/2021 to 03/31/2021 and was funded by a grant from the California Department of Transportation (Caltrans) in the amount of $99,604. The research was conducted as part of the Pacific Southwest Region University Transportation Center research program.

Abstract

The purpose of this project is to measure the magnitude of the pollution reduction co-benefit generated by pricing congestion. Specifically, we estimate two empirical models: First, a model that examines the effects of traffic congestion, measured by cars per miles, on NO and NO2 emissions of vehicles in freeways. Second, a model that relates speed with NO and NO2 emissions from vehicles on local roads. Our results suggest important relationships between traffic congestion and NO and NO2 in both freeways and local roads, and results are reported for different time periods. Such estimates can serve as an important input in order to calculate the pollution benefits of congestion pricing. Therefore, we take our estimates and illustrate the pollution benefits from removing vehicles from the freeways. For example, removing 500 cars in the morning peak in a typical freeway translates roughly into a 10% reduction of NO emissions in freeways.

Research Report

Executive Summary

Los Angeles is now one of the global leaders in urban traffic congestion. On average, Angelinos spend 104 hours stuck in traffic each year. For a typical worker, this is equivalent to a total loss of 13 working days in a year. And, in total, the estimates of the social cost of traffic congestion in Los Angeles add up to $9.7 billion dollars per year, or $2,408 per driver. In response to this concern, LA's Metro board approved on February 28, 2019 a series of strategies for 're-imagining of LA County', which includes a congestion pricing feasibility study. With congestion pricing, drivers will see the price of their daily commutes increased, as they will be charged for the external costs of congestion in the form of increased delays. As a consequence, congestion pricing will create incentives for drivers to alter their commuting patterns, including adjusting the time of the commute, reducing overall vehicle miles traveled, and potentially even creating incentives for increased public transit usage. A direct co-benefit of congestion pricing is pollution reduction.

The purpose of this project is to measure the magnitude of the pollution reduction co-benefit generated by pricing congestion. In California, despite incentives for the adoption of cleaner vehicles and increased penetration of electric vehicles in the fleet, GHG emissions from transportation continue to increase. And when it comes to local air pollution, while tough regulations have certainly brought dramatic reductions in air pollution and improved health, Southern California remains the nation's smoggiest region, and continues to fail to meet federal Ozone standards. Regulators recognize that cleaning the air to federal standards will require a massive transformation of California's transportation sector. To date, however, these proposals have focused primarily on technology and ignored increased in vehicle miles traveled. In contrast, economists have long argued that policies that promote cleaner technological adoptions need to be matched with pricing policies that control vehicle miles traveled, and encourage drivers to find alternative ways to commute. Another reason to consider the pollution co-benefits of congestion pricing is that, even if starting in 2030 all new vehicle sales will have to be electric, it will take a long time to eliminate the existing gas-powered vehicles from the fleet.

Understanding the potential pollution benefits of congestion pricing requires a careful understanding of the empirical relationship between pollution, traffic congestion, and speed. We have put together the most comprehensive 'big data' to estimate two models. First, a model that examines the effects of traffic congestion, measured by cars per miles, on NO and NO2 emissions of vehicles in freeways. Second, a model that relates speed with NO and NO2 emissions from vehicles on local roads. Our dataset includes data on a rich network of detectors located on the freeways in Los Angeles that measure speed and flow in real-time, and novel and unexploited data from Aclima that measures in real-time the concentrations of various local air pollutants (including NO, NO2, Ozone, and Black Carbon). In this project we focus on NO, and NO2, since it is relatively easy to recover casual effects of traffic congestion on these pollutants. Unlike Ozone, which is formed through the combination of NOx, VOCs and sunlight, NO comes directly off the tailpipe. Given its short-live, once it reacts NO transforms in NO2. At the point of emission (i.e. exhaust pipe), the proportion of NOx is around 90% NO and 10% NO2. After a few hours in the atmosphere in the presence of volatile organic compounds (VOCs) the NO is converted to NO2. This reaction can occur over a couple of seconds to a few hours. Aclima data was collected for 3 months, relying on pollution sensors on Google cars that drive repeatedly across different freeways and local roads.

We apply econometric techniques to estimate the effects of traffic density on pollution, and data visualization methods to display key patterns in the data useful for policymakers to prioritize areas of intervention. When calculating the marginal effects of cars per mile on pollution, we report results by geographical area and explore the role of past hours traffic on pollution in the following hours, effects of traffic on accumulated pollution, and the role of weather variables on the magnitude of the effects.

Our results suggest important relationships between traffic congestion and NO and NO2 in both freeways and local roads, and results are reported for different time periods. Such estimates can serve as an important input in order to calculate the pollution benefits of congestion pricing. Therefore, we take our estimates and illustrate the pollution benefits from removing vehicles from the freeways.

Introduction

Los Angeles is now one of the global leaders in urban traffic congestion. On average, Angelinos spend 104 hours stuck in traffic each year. For a typical worker, this is equivalent to a total loss of 13 working days in a year. And, in total, the estimates of the social cost of traffic congestion in Los Angeles add up to $9.7 billion dollars per year, or $2,408 per driver. In response to this concern, LA's Metro board approved on February 28, 2019 a series of strategies for 're-imagining of LA County', which includes a congestion pricing feasibility study. With congestion pricing, drivers will see the price of their daily commutes increased, as they will be charged for the external costs of congestion in the form of increased delays. As a consequence, congestion pricing will create incentives for drivers to alter their commuting patterns, including adjusting the time of the commute, reducing overall vehicle miles traveled, and potentially even creating incentives for increased public transit usage. A direct co-benefit of congestion pricing is pollution reduction.

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Understanding the potential pollution benefits of congestion pricing requires a careful understanding of the empirical relationship between pollution, traffic congestion, and speed. We have put together the most comprehensive 'big data' to estimate two models. First, a model that examines the effects of traffic congestion, measured by cars per miles, on NO and NO2 emissions of vehicles in freeways. Second, a model that relates speed with NO and NO2 emissions from vehicles on local roads. Our dataset includes data on a rich network of detectors located on the freeways in Los Angeles that measure speed and flow in real-time, and novel and unexploited data from Aclima that measures in real-time the concentrations of various local air pollutants (including NO, NO2, Ozone, and Black Carbon). In this project we focus on NO, and NO2, since it is relatively easy to recover casual effects of traffic congestion on these pollutants. Unlike Ozone, which is formed through the combination of NOx, VOCs and sunlight, NO comes directly off the tailpipe. Given its short-live, once it reacts NO transforms in NO2. At the point of emission (i.e. exhaust pipe), the proportion of NOx is around 90% NO and 10% NO2. After a few hours in the atmosphere in the presence of volatile organic compounds (VOCs) the NO is converted to NO2. This reaction can occur over a couple of seconds to a few hours (Zhong, 2017). Aclima data was collected for 3 months, relying on pollution sensors on Google cars that drive repeatedly across different freeways and local roads.

We apply econometric techniques to estimate the effects of traffic density on pollution, and data visualization methods to display key patterns in the data useful for policymakers to prioritize areas of intervention. When calculating the marginal effects of cars per mile on pollution, we report results by geographical area and explore the role of past hours traffic on pollution in the following hours, effects of traffic on accumulated pollution, and the role of weather variables on the magnitude of the effects.

Our results suggest important relationships between traffic congestion and NO and NO2 in both freeways and local roads, and results are reported for different time periods. Our central results point to an elasticity of emissions with respect to traffic congestion in the order of 0.223 and 0.136 for NO and NO2 in the morning peak in freeways. That is an increase in 1% of cars per mile in the morning peak (roughly 11 vehicles) results in a 0.223 percent increase in NO (roughly 0.2712 ppb). Such estimates can serve as an important input in order to calculate the pollution benefits of congestion pricing. Therefore, we take our estimates and illustrate the pollution benefits from removing vehicles from the freeways. For example, removing 500 vehicles during the morning peak in a representative freeway results in a reduction of roughly 10% in NO. Results for NO2 are consistent with these patterns.

To understand these results note that traffic levels affect pollution through different channels. First, an increase in the number of cars on the freeway at any given time results in more fuel burned, and pollution. Second, traffic congestion can increase the amount of pollution each individual car creates. Efficiency of automobile combustion is directly related to average travel speed and continuity of driving (Davis and Diegel, 2007), and engines have an optimal revolution per minute (RPM) range in which they obtain the maximum amount of power for any given amount of fuel. Thus, stop-and-go traffic means fluctuations in the engine revolutions per minute and less time within the optimal RMP range. Finally, traffic congestion can decrease the average speed on each vehicle on the road. At a given revolution per minute (and engine efficiency), a slower speed implies more time on the road to travel the same distance, and this more fuel burned for each mile traveled. To attempt to understand the role of these channels we run models that allows for flexibility through bins in speed.

Data

Data Sources

To measure the effects of traffic congestion on pollution, we have put together a comprehensive dataset. The data has 3 major components:

A. *Aclima data*

Using a mobile measurement technique pioneered by Aclima, we rely on real-time measurements of emissions collected by two Aclima/Google cars as they drove around Los Angeles. The resulting hyperlocal data produced by Aclima's mobile system helps efforts by identifying problematic hot spots typically not captured by regional monitoring, allowing for visualizing patterns on the neighborhood and community scale, and measuring the effects of programs and policies that aim to reduce pollution at the local level. One could be concerned that the Aclima readings capture emissions from other sources other than vehicular emissions. Similarly, one could be concerned that, depending on the location, weather could affect the readings. Below, when discussing the empirical strategy, we argue that, with various fixed-effects, our statistical model addresses these concerns.

We have data for 3 consecutive months, covering August to October 2019. While the cars drove around Los Angeles, they did sample heavily on five communities: urban inland neighborhoods near major freeways; residential areas near the Pacific Ocean; Communities located near the port and refinery regions; and downtown Los Angeles. Some of these communities, including downtown Los Angeles and Santa Monica are priority areas for potential congestion pricing pilot projects. The sampling from Boyle Heights and Wilmington – two environmental justice neighborhoods permits an examination of the disproportionate impacts of traffic congestion on these neighborhoods. North Long beach and Westchester are also interesting sites, given that they are just north of the Los Angeles International Airport.

The Aclima cars drove from Monday through Friday during typical work hours of 6AM to 6PM. We have aggregated the readings in 5 minutes intervals and 3-digit latitude and longitude. Figure 2 and Figure 4 display the locations of observations by time periods.

In addition to collecting readings on NO, NO2, Ozone and black carbon, based on the latitude and longitude of the readings and their timestamps, we are also to recover a measure of the car speeds. Readings come from Freeway and local roads, and below we estimate separate models for these.

Freeway Performance Management System (PEMS) data:

Aclima data is completed with data from PEMS. In particular when Aclima cars are on freeways, we matched Aclima data with PEMS. For each point in the Aclima data on freeways, we merge it with nearest PEMS monitor and obtain measures of road traffic, including speed and flow. As a result, for freeways, we are able to construct a measure of cars per mile, which captures volume of traffic. In contrast, for local roads, we can only rely on the speed constructed based on the Aclima cars, since we don't have data on flow.

Other data:

Weather data comes from the National Weather Service. Weather data includes, amongst others, temperature, humidity, and wind speed. The relationship between vehicular traffic and air pollution is complex and interacts with local meteorology. For example, NO2 is formed by reaction of NO emitted by vehicles and oxygen in the atmosphere, and is itself a precursor to other harmful pollutants such as Ozone (Zhong, 2017). It is also well known that thermal inversions can affect pollution, contributing to the accumulation of pollutants and trapping them near the ground (Wallace et al, 2010; Bailey et al, 2011; South Coast Air Quality Management District, 2017).

For each Aclima point, we find the eight nearest weather stations in LA county, and rank those in ascending order of the distance to the point. After that, for each variable, if the weather reading on the nearest station was missing for a particular hour, we replace it by the weather reading of the second nearest station for that hour. We repeat that process with replacement by third and fourth nearest station until the observation on the variable is no longer missing or we have reached the eight station, whichever comes first.

Spatial Aggregation and Data Merging

For each point in the Aclima data, we link it to polygons of census block groups and assign the census block group ID. We group observations based on census block groups to assure that we have enough observations per group (see Figure 2 and Figure 4).

Figure 1 shows the pollution trends by each of the 5 locations, as well as our measure of cars per mile. The figure underscores some of the underlying heterogeneity in the data, confirming prior concerns that busier roads and freeways may generate disproportionate levels of pollution, that could be detrimental to public health (Levy et al, 2010; Knittel et al, 2016). While in some areas, such as North Long Beach pollution trends follow closely traffic, in others this is not necessarily the case. In downtown Los Angeles, for example, there appears to be a relatively weaker relationship between traffic and pollution, especially during the late morning and early afternoon.

Overall the figures suggest that the links between pollution and traffic appear to be linked with the hour of the data. As such we estimate models for 3 time periods: morning peak (6-10AM), morning off peak (10AM-2PM) and afternoon peak (2PM-6PM).

Figure 3 and Figure 6 show the distribution of speeds in freeways and local roads. And Figure 5 plots cars per mile against speed. This figure underscores an interesting shape for this relationship, which appears to be relatively flatter for speeds lower than 40MPh and downward slopping for higher speeds.

Methods

We begin by describing the empirical strategy utilized to estimate the effects of traffic on pollution. We estimate two models: a model that captures the effects of traffic, measured by vehicles per mile, on pollution in freeways; and a model that recovers the effects of speed on pollution on local roads. We remind the reader that, unlike freeways, we don't have data on volume of vehicles on local roads.

Models Estimated

a. Freeway Model

We employ a simple regression analysis where logged emissions readings in location i at time t is regressed on logged cars per mile in location i at time t interacted with speed bins, and a series of fixed effects. Pollution readers come from the Aclima cars and are aggregated at 5 minutes. To capture how speed affects pollution through the performance of the vehicle, we created three bins: less than 20 mph, 20-50 mph, and greater than 50mph. At speed less than 20 mph, vehicles are in heavy traffic and will stop-and-go from frequently. Between 20-50 mph vehicles are closer to their optimal performance, and at speeds greater than 50 mph performance is also sub-optimal due to acceleration. Here, performance of the vehicle refers to its engine performance. We include weather covariates, such as temperature, relative humidity, and wind speed; a measure of 10-minute lagged pollution to capture accumulation of pollution; fixed effects for hour of the day interacted with day of the week, to capture the fact that even for the same hour, traffic differs by day of the week; we also include month, google car, and freeway fixed effects. Standard errors are clustered at hour and freeway level. Our main specification is given by:

$$
\begin{aligned}
log(y_{it}) =& log(y_{i,t-1}) + log(CarsPerMile_{it}) \times SpeedBins_{it} \\
&+ HourDOW_{hd} + Month_m + Car_c + Freeway_f + \epsilon_{it},
\end{aligned}
$$

In this equation, Y_{it} represents emissions, and we run separate regressions for NO and NO_2.

b. Local Roads model

We run similar models for local roads, with the difference that in local roads we don't have from PEMS on cars per mile. So, we simply include speed bins based on speed readings from the Aclima cars. In the case of local roads, we are also interested in measuring the effects of traffic congestion in specific geographical areas, for which congestion pricing programs could be an option or in disadvantage areas where, due to truck traffic, pollution levels can be substantial higher. Therefore, for the local roads model, we present results broken down by two key regions: downtown Los Angeles, an area where congestion pricing is being considered, and Wilmington, a traditional neighborhood with environmental justice concerns. One should note that our statistical analysis includes a series of flexible fixed-effects to capture the variation in total emissions for the entire metropolitan region. As such, the coefficients of interest should be interpreted as the effect of traffic on pollution, after controlling for all other sources of pollution and weather conditions.

One may be concerned that there is substantially underlying heterogeneity in the coefficient of interest that the simpler model outline above would mask. For example, truck traffic may be heavier at certain hours of the day and certain locations. Similarly, pollution formation may be sensitive to both accumulation and interaction with weather. As such, in addition to the fixed effects mentioned above, we also run these models for three time periods: Morning Peak, corresponding to 6-10AM; Morning off-peak, corresponding to 10AM-2PM; and afternoon peak, corresponding to 2PM-6PM. Finally, even during these time periods there can still be a fair amount of heterogeneity. Therefore, we also run regressions for the 'peak of the peak', both in the morning and afternoon.

Results

Effects of Freeway Traffic on NO: Morning Peak

Table 1 presents the regression estimates of the effect of freeway traffic on NO. For each time period, the table reports the point estimate and standard error for the coefficient of interest. Given the log-log specification, the coefficient of interest here should be interpreted as an elasticity, that is the coefficient of interest reports the percentage change in pollution resulting from a one percent change in cars per mile.

We highlight the following results:

First let's focus on the morning peak, corresponding to the hours of 6-10AM. Starting with the middle speed (20-50 Mph) row, a one percent change in cars per miles results in an 0.223 percent increase in NO emissions. The point estimate is statistically significant at the 5 percent level. Second, this point estimate drops to 0.169 when we consider the highest speed bin (50+Mph). The differences in these two point estimates are driven by the total cars per mile in each of the bin, as well as the speed of each car. When speed ranges between 20-50 mph, there is overall more traffic. Therefore, to drive the same distance, vehicles spend relatively more time in operation, and thus generate more emissions. At the same time, at these speeds, vehicles are closer to their optimal performance. Therefore, and unlike the other bins, emissions per vehicle should be lower. When a vehicle moves from the middle to the higher bin, one would expect pollution per vehicle to increase, since for speeds greater than 50 Mph, vehicles will now be accelerating. The comparison between these two point estimates suggest that having a vehicle longer in operation (for the same distance) is likely to be relatively more important to emissions than having a vehicle accelerating. We will return to this issue, when below we will further interpret these results and present them in terms of contribution of car to pollution. Here we simply note that these heterogeneities are critical parameters to inform the design of congestion pricing programs.

At first glance, it may be surprising that the point estimate for the speed bin below 20 Mph is lower than the middle bid. After all, one would have expected that at lower speeds pollution would be particularly higher. Recall that at lower speeds, there is overall more cars per mile, trips take longer for the same distance, and each car performance is sub-optimal. While this is all true, we note that, unfortunately, there is simply not sufficient variation in the data to identify this effect. We should therefore, interpret this estimate with caution, and likely think of it as an underestimate of the true value for this bin. In fact, if nothing, the true estimate should be above that of the middle bin.

Effects of Freeway Traffic on NO: Heterogeneity across hours of the day

Interestingly, as we compare the results across time periods (that is, moving horizontally on Table 1), we note that the point estimates roughly double. For example, in the middle bin, as we move from the morning peak (6-10AM) to early afternoon (10-2PM), the point estimate grows from 0.170 to 0.409. Interestingly, the value of the estimate later in the day (2PM-6PM) is more aligned with the morning peak. The higher results between 10-2PM are likely attributed to weather patterns and the composition of traffic. We are still exploring further sensitivity analysis to fully interpret these differences.

Effects of Freeway Traffic on NO: Results at the 'peak of the peak'

We have also estimated the basic model, focusing exclusively at the peak of the peak. Specifically, we examined the effects at 9AM and 5PM. These are reported in Table 3. Broadly speaking, we note that the point estimates of the second and third speed bins are only slightly higher than those reported in Table 1, albeit not statistically different from one another.

Effects on Local Roads: NO and NO2

We also estimate models of the effects of traffic congestion, measured by the speed (of Aclima Cars) on pollution on local roads. We remind the reader that, unlike the models on freeways where we had measures of cars per mile (coming from PEMS), such data doesn't exist for local roads. Of course, the limitation of this model is that we implicitly assume that under a no-congestion scenario the collector vehicle would be bound to the legal speed limit. Nonetheless it is still instructive understanding the relationship between speed and pollution. These models are similar in structure with the models on freeways with two important differences. First, we use speeds. Second, given important spatial heterogeneity, we also include block group fixed effects.

The results are reported on Table 4 and Table 5, for NO and NO2 respectively. A comparison of the NO results reveals one major difference. The estimate of the speed bin 50+ is now larger than the middle speed bin. This suggests that in local roads the effects of speeding on pollution, due to vehicles operating sub-optimal, appear to be a bigger concern. For example, in the morning peak, as we move from the middle to the highest speed bin, the coefficient moves from 0.077 to 0.098. And the wedge between the two is even more pronounced during the late morning/early afternoon period. (0.051 versus 0.229).

The results for NO2, reported on Table 5, also reveal interesting patterns. While in freeways, the coefficients were always significant during the morning peak, in the case of NO2 in local roads the effects are either insignificant or barely significant (for the middle bin). In contrast, they are very significant in the following time periods. Together this is perhaps suggestive that the conversion of NO to NO2 is slower in local roads. This result deserves further examination in future research.

Effects on Local Roads: Spatial Heterogeneity

It is informative to examine the heterogeneity of the effects in local roads across space. In particular, we examined the effects in downtown Los Angeles, an area that is being considered under the current pilot congestion pricing; we also examined the effects in Wilmington, a neighborhood with environmental justice concerns.

Table 6 and Table 7 shows the NO and effects in downtown LA and Wilmington, respectively. Two interesting results emerge. First, relatively to the previous table, the estimates are relatively lower in downtown LA, especially during the morning peak (0.058 versus 0.077). Second, the effects in Wilmington are particular revealing. It appears that the key insight is that the effect is the largest in the highest bin (speeds 50+Mph). This is suggestive that congestion is perhaps less a concern in this neighborhood. Rather the much higher point estimates are likely to be driven by the composition of the fleet, since we suspect that heavy trucks pass more frequently through this neighborhood. That explains the estimate in the morning peak of 0.342, many orders of magnitude higher than in the 'average' model (0.057). The community of Wilmington is close to the Port of Long Beach and LA. Goods are transported to and from the Ports by ships, trains and heavy-duty trucks. Trucks travel along freeways (e.g. I-710, I-110, I-405, ad I-91) nearby Wilmington. Further, trucks often travel near and through local neighborhoods to reach their destinations. We should be careful with the interpretation of these results. While we are attributing the results to traffic in local roads, it is still likely that part of the effect comes from the density of freeways nearby and the heavy trucks in these freeways. Disentangling those effects presents many challenges beyond the scope of this project.

Pollution benefits from Congestion Pricing Programs

The models of the effects of traffic congestion in freeways and local roads on pollution provide a first order parameter to inform the pollution benefits from congestion pricing. Of course, to fully measure such benefits, one would need to develop a structural model of commuting decisions. Consider an individual making traveling decisions. This individual decides the departure time, and the route (including whether to drive on the freeway, local roads or both). Faced with a pricing policy on congestion, this individual can either adjust departure times (to avoid higher congested times, where the tolls will likely be higher), replace all his driving on freeways by driving on local roads. Or, importantly, reduce the amount of driving and substitute it by trips in other transportation modes, such as public transit. While it is beyond the scope of this project to consider all these decisions, our estimates provide a first assessment of the potential pollution reductions in freeways and nearby them that would result from removing vehicles from these freeways. Of course, absence of a structural transportation model, we are unable to infer whether such trips would appear anywhere else in the transportation system.

To highlight the use of the estimated models here, we proceed as follows: First, we produced descriptive statistics of the levels of NO, NO2 and cars per mile for the different bins and time periods (morning peak, morning off-peak, afternoon peak). Second, we use the point estimates from Table 1 to calculate the marginal contribution of a vehicle to pollution. Finally, combining this information allow us to infer the potential pollution reduction that would happen if we were to remove from a typical freeway the number of cars to eliminate congestion. We focus our analysis on freeways, since it is unlikely that congestion pricing will apply to local roads.

Table 8 reports summary statistics across speed bins and time periods in freeways. Echoing some of the descriptive statistics figures discussed earlier, the table highlights the heterogeneity of baseline pollution and cars per mile. NO and NO2 values are at their highest in the morning peak for speeds between 20-50 Mph. The table also highlights some of the variability in cars per mile across the different bins and time periods.

Table 9 reports the marginal effects, that is the additional pollution resulting from adding an additional car on freeways at different speed bins and time periods. These marginal effects are calculated based on the estimates from Table 8.

The table underscores that the contribution of a vehicle to pollution is very much dependent on the speed bin and time period. For example, the contribution of a vehicle to NO takes its highest value in the afternoon in the speed bin 50+ MhP (0.0434).

With the information in these tables, we can now conduct the following exercise. Suppose that as a result from congestion pricing, vehicles are removed from freeways at different times periods. Suppose that to eliminate congestion one typically needs to remove 500-700 cars per mile during the morning peak. Removing them would result in a 12.1 ppb drop in NO, which is roughly 10% reduction in NO emissions, if these vehicles were not to appear in other locations or other time periods. This value should be interpreted as the upper bound effect on reduction in pollution. Of course, even if some of these vehicles re-appear in the transportation system, pollution still disperses and that too can represent a potential gain. To the extent that vulnerable communities locate closer to freeways, congestion pricing is likely to yield large benefits to these communities.

Conclusions

We have put together a unique data set consisting of real-time pollution measurements from Aclima cars that capture pollution readings in freeways and local roads. We coupled this data with PEMS data to estimate models of the effects of traffic congestion on pollution. Our results underscore the importance of new sources of big data to inform the design of congestion pricing policies, and our models demonstrate non-trivial pollution effects of adding (removing) vehicles from freeways. In the end, from a pollution perspective, congestion pricing in freeways likely assures that, at time where congestion tolls are higher, individuals will substitute away from freeways. Our central estimates imply that in the morning NO can reduce as much as 10% as a result of congestion pricing. Future work, however, should consider coupling our estimates with transportation models to further infer the effects of congestion pricing to the entire transportation system.

Table 1. The Effects of Freeway Traffic on NO

	Dependent variable: log(NO)								
	6AM - 10AM			10AM - 2PM			2PM - 6PM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(no_lag1)	0.309*	0.287*	0.220**	0.172	0.130	0.159	0.275**	0.285**	0.251**
	(0.105)	(0.072)	(0.045)	(0.113)	(0.128)	(0.122)	(0.071)	(0.072)	(0.074)
log(car_mile):speed_bin<20	0.155**	0.174**	0.170**	0.355***	0.391***	0.409***	0.143**	0.147**	0.154**
	(0.032)	(0.022)	(0.025)	(0.043)	(0.046)	(0.066)	(0.037)	(0.027)	(0.032)
log(car_mile):speed_bin20-50	0.234**	0.221**	0.223**	0.339***	0.397***	0.418***	0.208***	0.213***	0.213***
	(0.029)	(0.036)	(0.034)	(0.031)	(0.022)	(0.044)	(0.034)	(0.033)	(0.031)
log(car_mile):speed_bin50+	0.189***	0.171**	0.169**	0.349***	0.444***	0.470***	0.173***	0.154***	0.154***
	(0.015)	(0.030)	(0.027)	(0.036)	(0.031)	(0.060)	(0.021)	(0.018)	(0.026)
Hour	Yes	No	No	Yes	No	No	Yes	No	No
DOW	Yes	No	No	Yes	No	No	Yes	No	No
Hour-DOW	No	No	Yes	No	No	Yes	No	No	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Car Identifier	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Freeway	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,074	2,074	2,074	1,569	1,569	1,569	1,470	1,470	1,470
R^2	0.410	0.442	0.461	0.210	0.266	0.279	0.169	0.206	0.227
Adjusted R^2	0.406	0.434	0.452	0.203	0.250	0.257	0.161	0.189	0.206

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2. The Effects of Freeway Traffic on NO2

	Dependent variable: log(NO_2)								
	6AM - 10AM			10AM - 2PM			2PM - 6PM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(no2_lag1)	0.291	0.209	0.202	0.187	0.132	0.147	0.553**	0.535**	0.523**
	(0.183)	(0.138)	(0.147)	(0.134)	(0.104)	(0.103)	(0.109)	(0.111)	(0.127)
log(car_mile):speed_bin<20	0.076***	0.088**	0.086**	0.213***	0.268**	0.271**	0.072	0.098*	0.085
	(0.005)	(0.016)	(0.016)	(0.029)	(0.069)	(0.077)	(0.032)	(0.032)	(0.041)
log(car_mile):speed_bin20-50	0.111***	0.104**	0.105**	0.213***	0.284**	0.286**	0.106**	0.128**	0.114**
	(0.004)	(0.021)	(0.022)	(0.026)	(0.062)	(0.067)	(0.029)	(0.029)	(0.036)
log(car_mile):speed_bin50+	0.083**	0.077**	0.077**	0.213***	0.306**	0.308**	0.087*	0.104*	0.093
	(0.015)	(0.018)	(0.017)	(0.027)	(0.071)	(0.078)	(0.032)	(0.036)	(0.041)
Hour	Yes	No	No	Yes	No	No	Yes	No	No
DOW	Yes	No	No	Yes	No	No	Yes	No	No
Hour-DOW	No	No	Yes	No	No	Yes	No	No	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Car Identifier	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Freeway	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,122	2,122	2,122	1,623	1,623	1,623	1,520	1,520	1,520
R^2	0.444	0.482	0.484	0.246	0.313	0.318	0.515	0.542	0.553
Adjusted R^2	0.441	0.475	0.476	0.240	0.299	0.299	0.511	0.533	0.542

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3. The Effect of Freeway traffic on NO at the Peak of the Peak

	Dependent variable: log(NO)					
	9AM		1PM		5PM	
	(1)	(2)	(3)	(4)	(5)	(6)
log(no_lag1)	0.228**	0.201	0.376***	0.412***	−2.558***	−2.586**
	(0.103)	(0.117)	(0.089)	(0.123)	(0.257)	(0.270)
log(car_mile):speed_bin<20	0.075	0.133*	0.528*	0.692		
	(0.070)	(0.064)	(0.299)	(0.494)		
log(car_mile):speed_bin20-50	0.173**	0.225***	0.607*	0.795	1.308***	1.311***
	(0.068)	(0.058)	(0.313)	(0.511)	(0.067)	(0.069)
log(car_mile):speed_bin50+	0.159***	0.176***	0.614*	0.790	1.171***	1.177***
	(0.056)	(0.041)	(0.320)	(0.507)	(0.079)	(0.083)
Hour	Yes	Yes	Yes	Yes	Yes	Yes
DOW	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes
Car Identifier	Yes	Yes	Yes	Yes	Yes	Yes
Freeway	No	Yes	No	Yes	No	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,470	1,470	300	300	106	106
R^2	0.323	0.341	0.239	0.268	0.585	0.592
Adjusted R^2	0.318	0.331	0.210	0.209	0.564	0.563

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4. The Effect of speed in local roads on NO

	Dependent variable: log(NO)								
	6AM - 10AM			10AM - 2PM			2PM - 6PM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(car_speed_trans):speed_bin<20	0.029	0.057	0.058	−0.024*	−0.002	−0.001	0.040	0.040**	0.038**
	(0.036)	(0.035)	(0.036)	(0.009)	(0.009)	(0.009)	(0.021)	(0.012)	(0.011)
log(car_speed_trans):speed_bin20-50	0.133***	0.077**	0.077**	0.071**	0.051**	0.051**	0.130***	0.062***	0.057***
	(0.021)	(0.021)	(0.022)	(0.016)	(0.013)	(0.014)	(0.011)	(0.006)	(0.005)
log(car_speed_trans):speed_bin50+	0.321***	0.099**	0.098**	0.363***	0.228***	0.229***	0.340***	0.105***	0.098***
	(0.052)	(0.027)	(0.028)	(0.043)	(0.030)	(0.029)	(0.028)	(0.012)	(0.014)
Hour	Yes	No	No	Yes	No	No	Yes	No	No
DOW	Yes	No	No	Yes	No	No	Yes	No	No
Hour-DOW	No	No	Yes	No	No	Yes	No	No	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Car Identifier	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BG	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,073	36,073	36,073	80,463	80,463	80,463	23,747	23,747	23,747
R^2	0.192	0.470	0.477	0.102	0.273	0.275	0.077	0.349	0.355
Adjusted R^2	0.191	0.459	0.466	0.102	0.266	0.267	0.077	0.331	0.336

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5. The effects of speed on local roads on NO2

Table

	Dependent variable: log(NO_2)								
	6AM - 10AM			10AM - 2PM			2PM - 6PM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(car_speed_trans):speed_bin<20	0.006	0.025	0.025	−0.004	0.005	0.005	0.011	0.019***	0.016***
	(0.019)	(0.016)	(0.016)	(0.005)	(0.004)	(0.004)	(0.009)	(0.003)	(0.002)
log(car_speed_trans):speed_bin20-50	0.056**	0.035*	0.035*	0.034**	0.029**	0.029**	0.059***	0.036***	0.031***
	(0.010)	(0.011)	(0.011)	(0.006)	(0.005)	(0.005)	(0.005)	(0.003)	(0.002)
log(car_speed_trans):speed_bin50+	0.126*	0.041	0.042	0.157**	0.113**	0.112**	0.151***	0.056***	0.052**
	(0.040)	(0.020)	(0.021)	(0.042)	(0.023)	(0.022)	(0.021)	(0.005)	(0.009)
Hour	Yes	No	No	Yes	No	No	Yes	No	No
DOW	Yes	No	No	Yes	No	No	Yes	No	No
Hour-DOW	No	No	Yes	No	No	Yes	No	No	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Car Identifier	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BG	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,553	36,553	36,553	82,318	82,318	82,318	25,837	25,837	25,837
R^2	0.146	0.545	0.551	0.095	0.427	0.432 7 0.110	0.566	0.579	
Adjusted R^2	0.145	0.535	0.542	0.095	0.422	0.426	0.110	0.555	0.568

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6. The effect of speed in local roads on NO: Downtown LA

	Dependent variable: log(NO)								
	6AM - 10AM			10AM - 2PM			2PM - 6PM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(car_speed_trans):speed_bin<20	−0.006	0.029	0.031	−0.029	−0.001	0.001	0.017	0.031	0.029
	(0.019)	(0.021)	(0.022)	(0.017)	(0.012)	(0.012)	(0.033)	(0.028)	(0.028)
log(car_speed_trans):speed_bin20-50	0.103***	0.057***	0.058***	0.055	0.041*	0.042*	0.065**	0.053**	0.049**
	(0.010)	(0.009)	(0.010)	(0.024)	(0.016)	(0.016)	(0.015)	(0.015)	(0.014)
log(car_speed_trans):speed_bin50+	0.274***	0.110*	0.118*	0.257**	0.129	0.120	0.324***	0.239**	0.221*
	(0.037)	(0.042)	(0.044)	(0.077)	(0.093)	(0.086)	(0.053)	(0.068)	(0.077)
Hour	Yes	No	No	Yes	No	No	Yes	No	No
DOW	Yes	No	No	Yes	No	No	Yes	No	No
Hour-DOW	No	No	Yes	No	No	Yes	No	No	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Car Identifier	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BG	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,130	19,130	19,130	33,069	33,069	33,069	13,107	13,107	13,107
R^2	0.165	0.366	0.388	0.081	0.210	0.216	0.057	0.173	0.181
Adjusted R^2	0.164	0.360	0.382	0.081	0.206	0.211	0.056	0.163	0.170

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7. The effect of speed in local roads on NO: Wilmington

	Dependent variable: log(NO)								
	6AM - 10AM			10AM - 2PM			2PM - 6PM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(car_speed_trans):speed_bin<20	0.056	0.059*	0.059*	−0.050	−0.029	−0.023 7	0.017	0.031	0.029
	(0.024)	(0.005)	(0.005)	(0.033)	(0.025)	(0.027)	(0.033)	(0.028)	(0.028)
log(car_speed_trans):speed_bin20-50	0.159	0.119	0.119	0.041	0.046	0.051	0.065**	0.053**	0.049**
	(0.042)	(0.021)	(0.021)	(0.039)	(0.033)	(0.034)	(0.015)	(0.015)	(0.014)
log(car_speed_trans):speed_bin50+	0.386*	0.342**	0.342**	0.175**	0.208**	0.205***	0.324***	0.239**	0.221*
	(0.033)	(0.012)	(0.012)	(0.055)	(0.045)	(0.030)	(0.053)	(0.068)	(0.077)
Hour	Yes	No	No	Yes	No	No	Yes	No	No
DOW	Yes	No	No	Yes	No	No	Yes	No	No
Hour-DOW	No	No	Yes	No	No	Yes	No	No	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Car Identifier	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BG	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Cluster SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,817	1,817	1,817	10,423	10,423	10,423	13,107	13,107	13,107
R^2	0.519	0.625	0.625	0.186	0.245	0.270	0.057	0.173	0.181
Adjusted R^2	0.517	0.615	0.615	0.185	0.240	0.264	0.056	0.163	0.170

Note: *p<0.1; **p<0.05; ***p<0.01

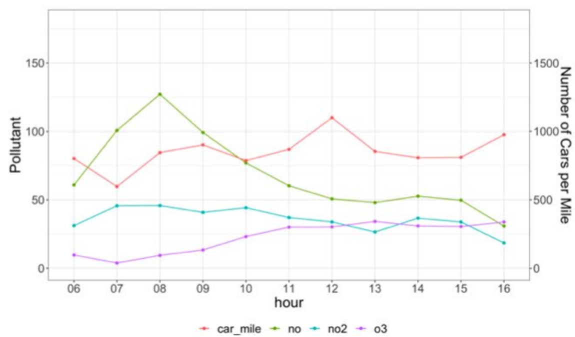
Table 8. Summary Statistics across speed bins and time periods in freeways

Speed Bin	Time	NO_2	NO	Cars Per Mile
<20	Morning Peak	39.31	80.11	1042.13
<20	Afternoon	30.53	49.36	1036.17
<20	Afternoon Peak	29.77	41.46	1212.14
20-50	Morning Peak	46.09	121.64	1120.94
20-50	Afternoon	36.70	66.34	1043.99
20-50	Afternoon Peak	36.78	62.69	1085.56
50+	Morning Peak	41.28	99.44	871.09
50+	Afternoon	35.67	58.80	637.39
50+	Afternoon Peak	30.16	42.25	617.47

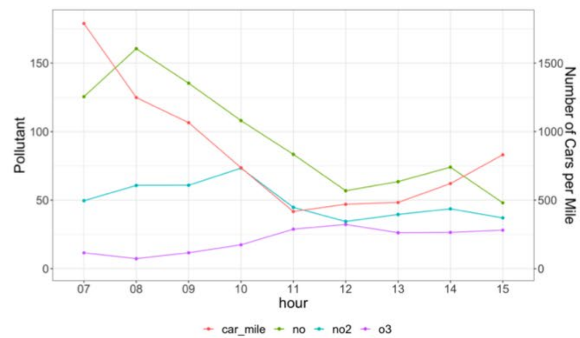
Table 9. Marginal Effects: Effects of adding on car on Pollution

Speed Bin	Time	NO_2	NO
<20	Morning Peak	0.0032	0.0131
<20	Afternoon	0.0080	0.0195
<20	Afternoon Peak	0.0021	0.0053
20-50	Morning Peak	0.0043	0.0242
20-50	Afternoon	0.0100	0.0266
20-50	Afternoon Peak	0.0039	0.0123
50+	Morning Peak	0.0036	0.0193
50+	Afternoon	0.0172	0.0434
50+	Afternoon Peak	0.0045	0.0105

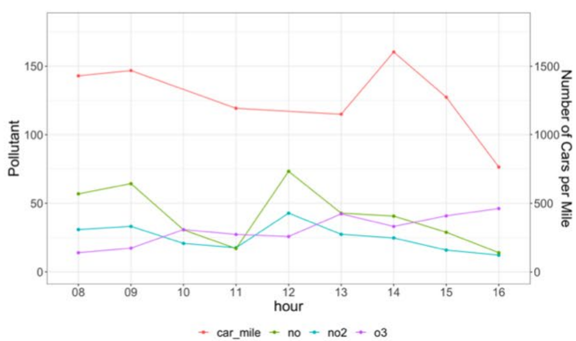
Figure 1. Distribution of pollution and Cars per Mile in different areas



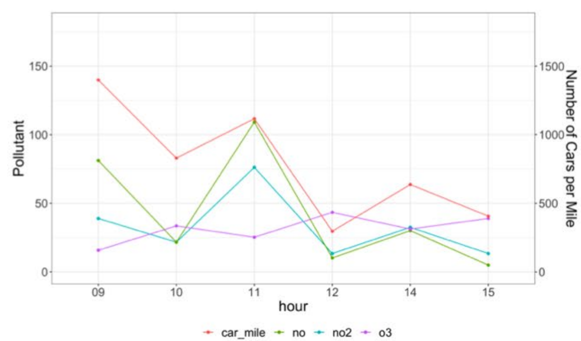
(a) DTLA



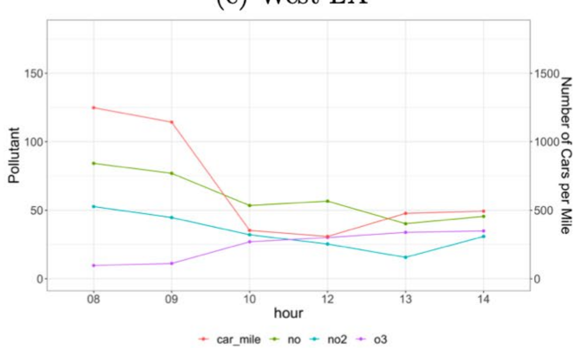
(b) North Long Beach



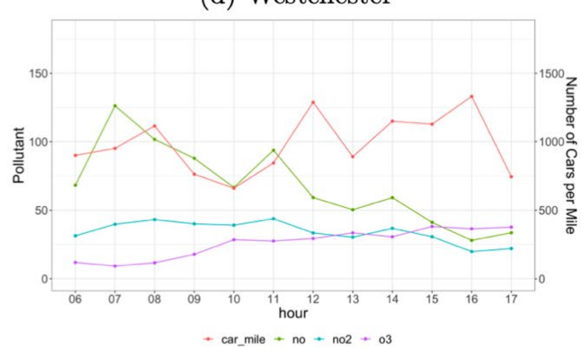
(c) West LA



(d) Westchester



(e) Wilmington



(f) Other

Figure 2. Distribution of pollution and Cars per Mile in different areas

(a) Morning Peak (6AM - 10AM)

(b) Afternoon (10AM - 14PM)

(c) Afternoon Peak (14PM - 18PM)

Figure 3. Distribution of speeds across time periods

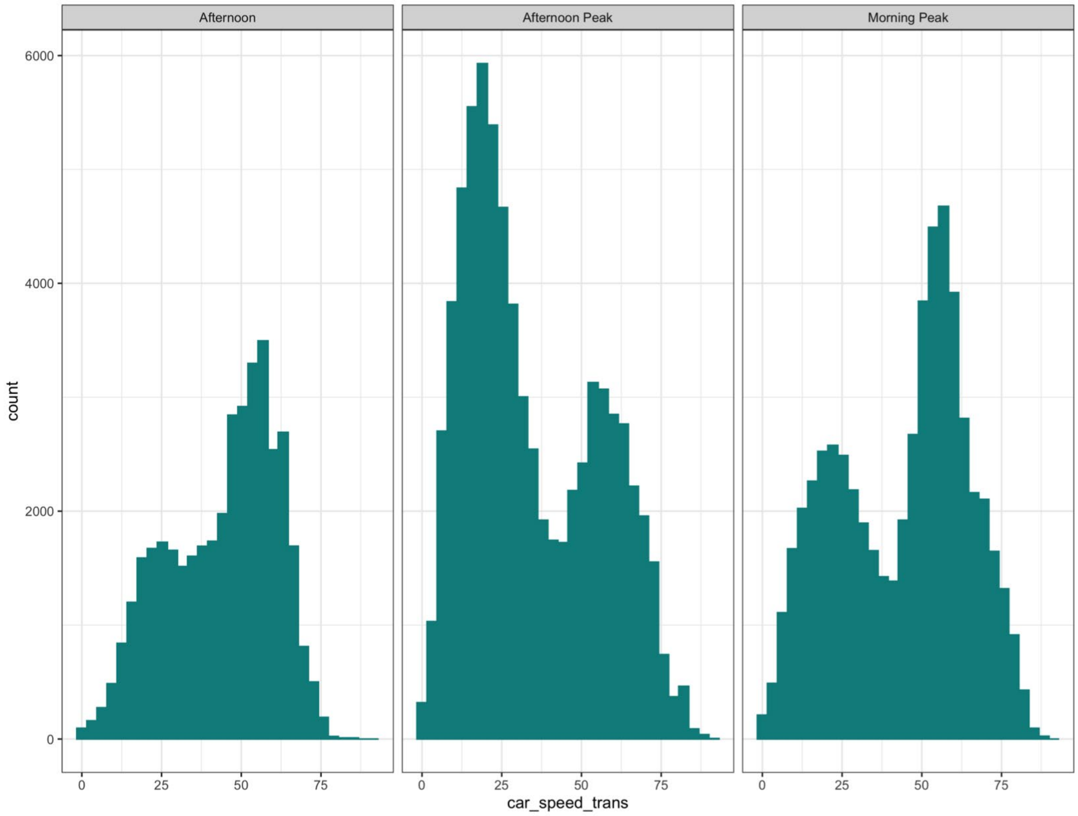
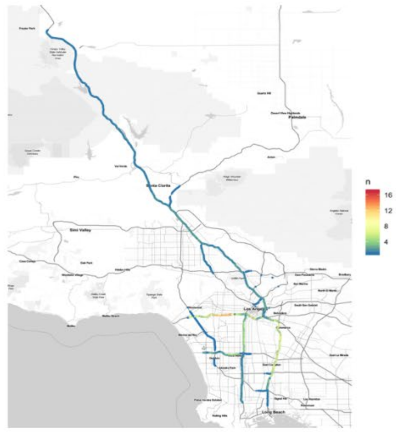
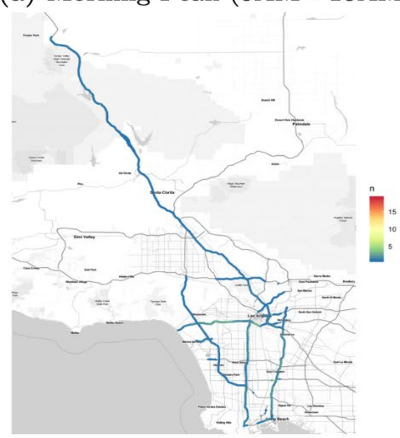


Figure 4. Number of observations (based on Aclima Cars) at different freeway locations



(a) Morning Peak (6AM - 10AM)



(b) Afternoon (10AM - 14PM)

(c) Afternoon Peak (14PM - 18PM)

Figure 5. Link between cars per mile and speed in Freeways

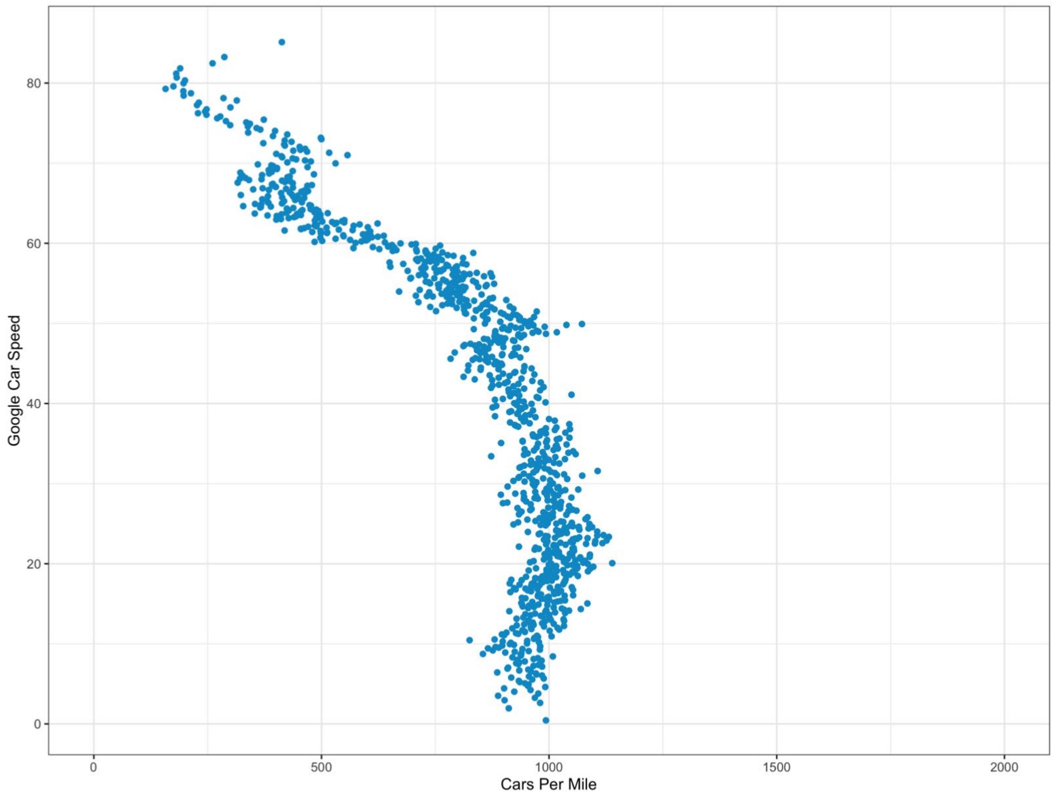
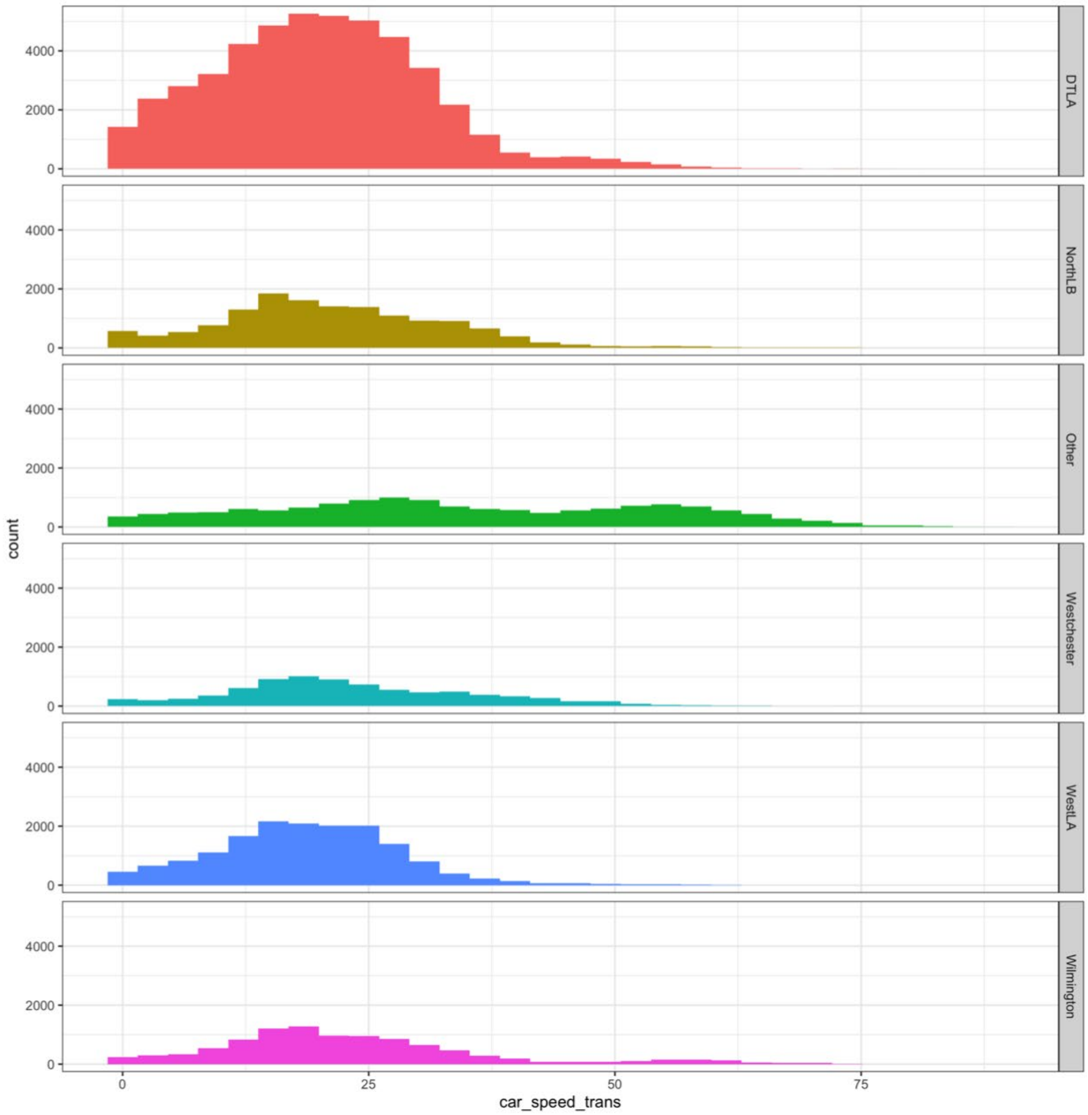


Figure 6. Distribution of speeds in local roads by area



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Data Management Plan

Products of Research

In the data section of the study we describe the data sources in details. These consist of 3 major datasets: real-time pollution readings in freeways and local roads by Aclima (restrictive data); PEMS data on speed and flows in freeways; Weather data.

Data Format and Content

Data was processed in Stata and R. All files that do not include restrictive data are available.

Data Access and Sharing

The exception of the Aclima data, all data is public and easily accessed.

Reuse and Redistribution

Use of the Aclima data requires approval by Aclima.