
Urban congestion relief experiments through routing-app interventions

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Supplementary Information

Mixed effects linear model

To further validate the efficacy of our intervention, we conduct an additional treatment effects evaluation through an alternative set of statistical models. We estimate a series of mixed-effects linear models (MLMs), where each outcome is modeled as a function of the chosen city, time of day, and switchback status, assuming independence between hourly observations as described in Equation (1), below. The MLM exercise provides transparency with respect to concerns that partial-pooling in the Bayesian model might overweight effects from other subgroups when reporting the effect on a given city or time of interest. This comes at the cost of precision as the MLMs have less information to draw on. However, as we show below, the qualitative agreement between the results from both sets of analyses suggests that the specific method used for estimation is not of first-order importance in our results.

For each outcome of interest y , we estimate the following mixed-effects linear model:

$$y_{c,h,t} = \beta_{\text{day}(t)} + \beta_{\text{pk}(h)} + \beta_{\text{day}(t),\text{pk}(h)} + \beta_{\text{sb}(h,t)} + \beta_{\text{sb}(h,t),\text{pk}(h)} + \eta_c + \eta_h h + \eta_{h^2} h^2 + \eta_{h^3} h^3 + \varepsilon_{c,h,t}. \quad (1)$$

Here, each observation is denoted by c , the city that the sample was collected from (e.g., Atlanta, Boston, etc.); h , the hour the observation was collected from; and t , the date of observation. To capture the variable trends across different cities, days, hours and regimes in a flexible way, our MLMs estimate a different fixed effect for the day of the week (“*day*”), peak status (“*pk*”), switchback status (“*sb*”) and the interaction between peak and weekday, and between peak and switchback. Peak status refers to whether the observation was during morning or afternoon peak times.¹ Switchback status refers to whether the observation took place during a treatment (“switchback on”) or control (“switchback off”) interval. In addition, we estimate a mean-zero random effect for each city c and coefficients on the level, square and cube of the hour of observation.

To conduct statistical inference with the MLMs, we perform randomization tests. To measure uncertainty, we run a placebo test in which the treatment path is randomly selected to generate a “placebo” dataset, and the effect size for this dataset is computed and compared with that of the ground truth treatment path. Figure 1 depicts this procedure. Whereas the true labeling of samples as from a treatment or control interval fluctuates periodically in each city, for each placebo run we instead randomly assign samples to the treatment and control groups and fit the MLM model based on this assignment. All samples from the same switchback interval, or 12pm to 12am intervals, are assigned the same treatment or control group. We then repeat this process 1000 times to determine the distribution of effect sizes that one would expect to see under random assignments. P-values in this setting are defined as the fraction of placebo runs that result in stronger point estimates for the considered outcome.

Distribution and proportion of rerouted trips

In this section, we attempt to quantify the proportion and properties of trips directly affected by the intervention. To do so, we characterize observed trips into subgroups defined in relation to the intervention. The subgroups considered are as follows. Groups 2 and 3 are exclusive, but group 1 includes elements of both.

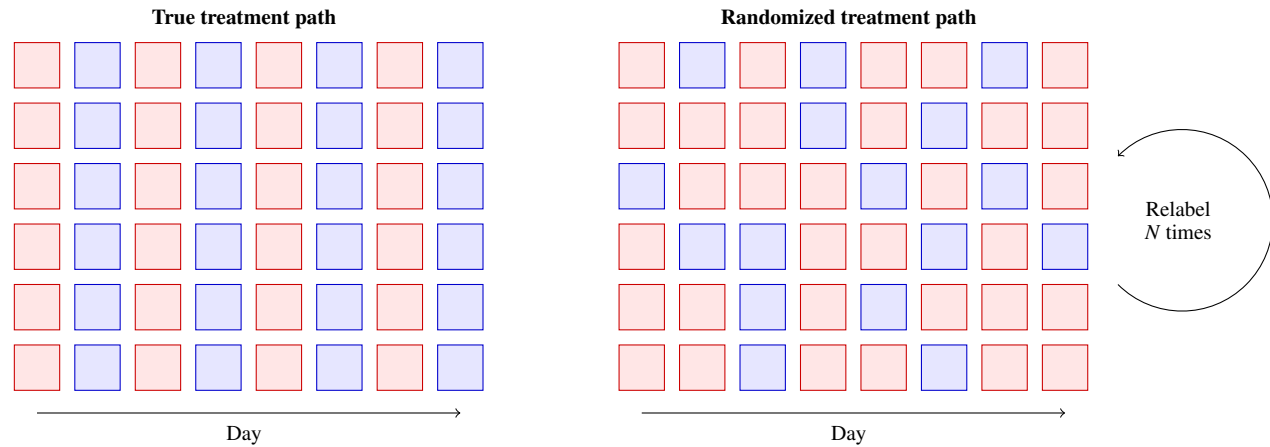
1. Trips passing through segments targeted by the intervention.
2. Trips that were rerouted based on our algorithmic targeting criteria during treatment periods, or would have been rerouted had they occurred during treatment periods.
3. Trips within the city that were not and would not have been rerouted.

Figures 8 and 9 depict the relative size of different subgroups and the distribution of travel times for each subgroup, respectively, in each city. Seen here, rerouted trips amount to a small fraction of trips passing through targeted segments (roughly 5 – 15%), and an even smaller fraction of total trips (< 2%). Moreover, each subgroup has a different distribution of trip characteristics. For instance, trips passing through targeted segments are generally longer than typical trips within a city. However, among trips passing through targeted segments, rerouted trips are typically shorter. These properties reflect the nature of the intervention: targeted segments were selected on the basis of identifiable metrics for congestion and were generally on highways or main arterials. As such, trips that pass through them tend to be longer in distance on average, but among those, trips with attractive alternatives may be on the shorter side.

Additional results

In this section, we present additional results aimed at answering specific questions regarding different factors influencing the intervention and provide a more robust set of findings to reinforce those presented in the main text.

¹We assume morning peaks are between the hours of 8:00 – 9:00, inclusive, and afternoon peaks between the hours of 15:00 – 18:00, inclusive.

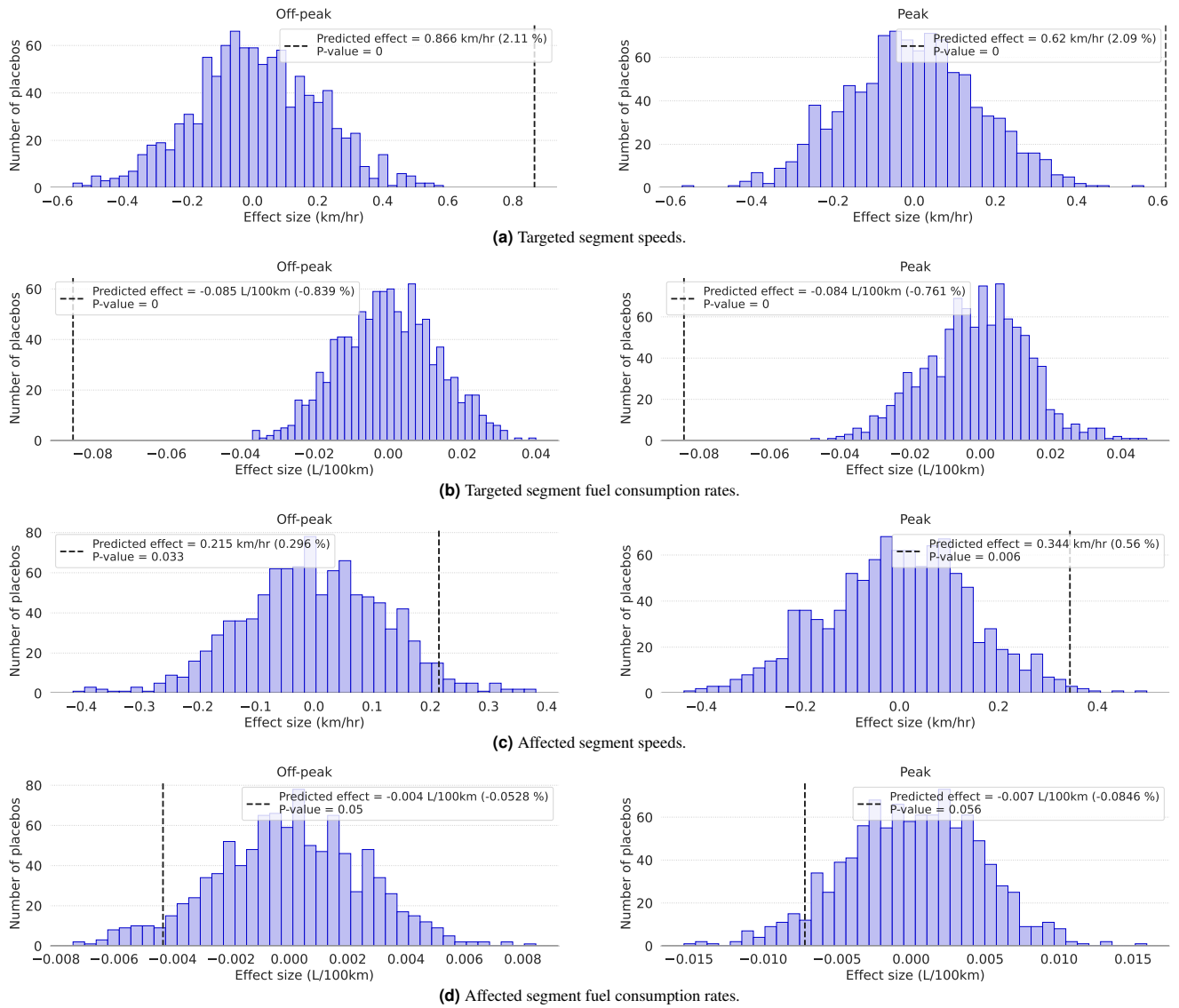


Supplementary Figure 1. Overview of the placebo study conducted alongside the mixed-effect linear model approach. We randomize the treatment path, i.e., whether an observation is labeled as from a treatment (blue) or control (red) interval, and use this placebo dataset to measure the impact from random assignments. We then repeat this process multiple times to approximate the variability in effect estimates under the null hypothesis.

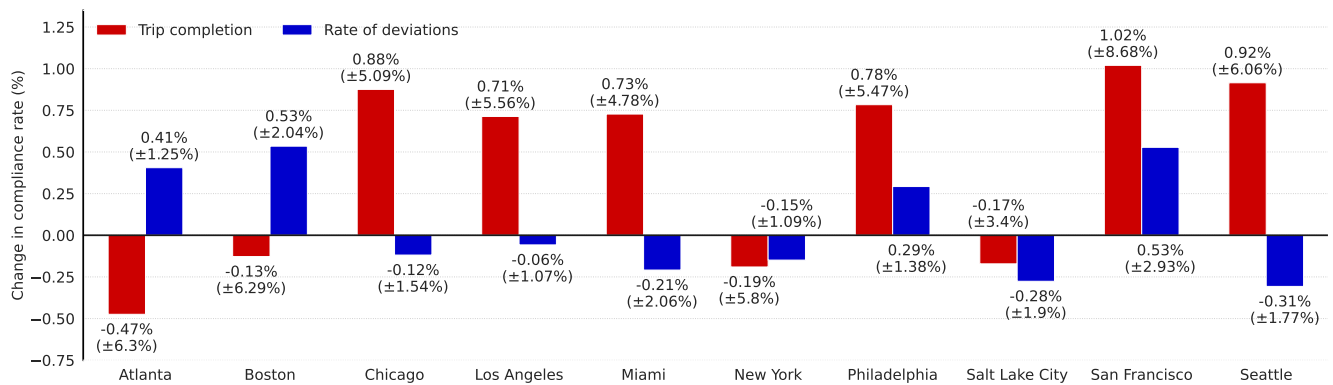
MLM findings We begin by replicating the findings presented in the main text through our MLM analysis. Analyses here are conducted across the same time window as utilized for the Bayesian hierarchical approaches in the main text. Figure 2 presents the impact on speeds and emissions rates for both targeted and affected segments as measured by the mixed-effects linear model. Separate point estimates are provided for peak and off-peak hours. In these figures, the vertical line represents the effect size as measured from the true switchback treatment assignments in the data, while the bar plots represent the distribution of measured effects from the placebo runs. Both the effect size and estimated P-values are provided in the legends of each figure. Seen here, point estimates produced by the mixed-effects linear model agree with the high-level findings presented by the Bayesian hierarchical modeling approach. We observe notable improvements to both speeds ($> 2\%$) and emission rates ($> 0.7\%$) on directly target segments. Moreover, these improvements persist when measured across all affected segments, with peak hours experiencing further improvements in efficacy compared to non-peak hours. Finally, as demonstrated through the placebo experiments, the effect size point estimates lie in the tails of distributions generated by random treatment paths ($P < 0.05$ in all cases). This confirms that our estimated effects are likely to be results of the intervention, and cannot be explained by random variability in traffic flow patterns or measurement error on specific segments.

Impact on trip guidance compliance Next, we measure the impact of the intervention on the trip experience of rerouted trips. To do so, we look at two measures of compliance: 1) trip completion, or the percentage of the trip followed by vehicles while using the routing service, and 2) rate of deviations, or percentage of maneuvers (e.g., “turn right”) performed without deviating or needing a new route to be assigned to them. For each of these measurements, we sample the compliance rate of rerouted trips in switchback on (treated) intervals, as well as of trips that would have been rerouted in switchback off (control) intervals had the intervention been active. This allows us to provide an apples-to-apples comparison of compliance rates between treated and non-treated trips. Figure 3 depicts the difference in compliance rates between rerouted and would-be rerouted trips under these two definitions. Seen here, compliance rates do not fluctuate significantly between subgroups in treatment and control intervals, generally keeping within a percentage point of one another in any given city. We also analyze the effect of our intervention on compliance using the daily model structure shown in Figure 10a. Our estimates show almost no effect at all, with a posterior probability of a negative effect of 54% for cities in which freeway segments were targeted and 38% for all other cities. The respective 95% credible intervals cover $(-0.006\%, +0.006\%)$ and $(-0.001\%, +0.001\%)$. The use of alternate routes, therefore, appears to produce no noticeable impact on the overall user experience for reaching desired destinations. To make sense of this result, recall that our intervention only affects the costs assigned to viable paths, but not the choice of viable paths themselves. As such, the “atypically” of proposed paths is likely sufficiently constrained by other processes upstream that it cannot result in substantive negative externalities for individual trips.

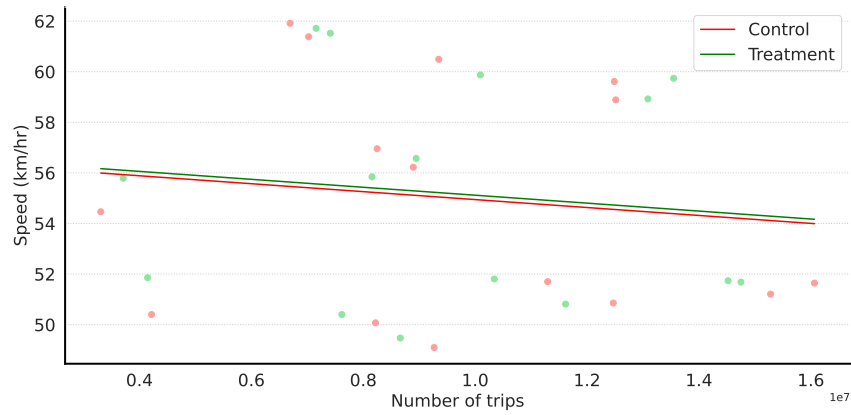
Effects of trip flows We consider the impact of trip flows on the qualitative results presented in this article. Here, we aim to answer the following question: Were the observed gains in speeds and emissions a (coincidental) result of fewer trips taken during switchback on periods? To answer this question, we look to the two month period for which individual trip observations were collected, and fit a linear model where observed daily speeds aggregated across all cities are estimated as a function of both switchback status and the number of observed trips for that given day. Figure 4 depicts the observed data points and the curves fit to the linear model. Seen here, trip counts do fluctuate substantially and driving speeds are indeed impacted by trip



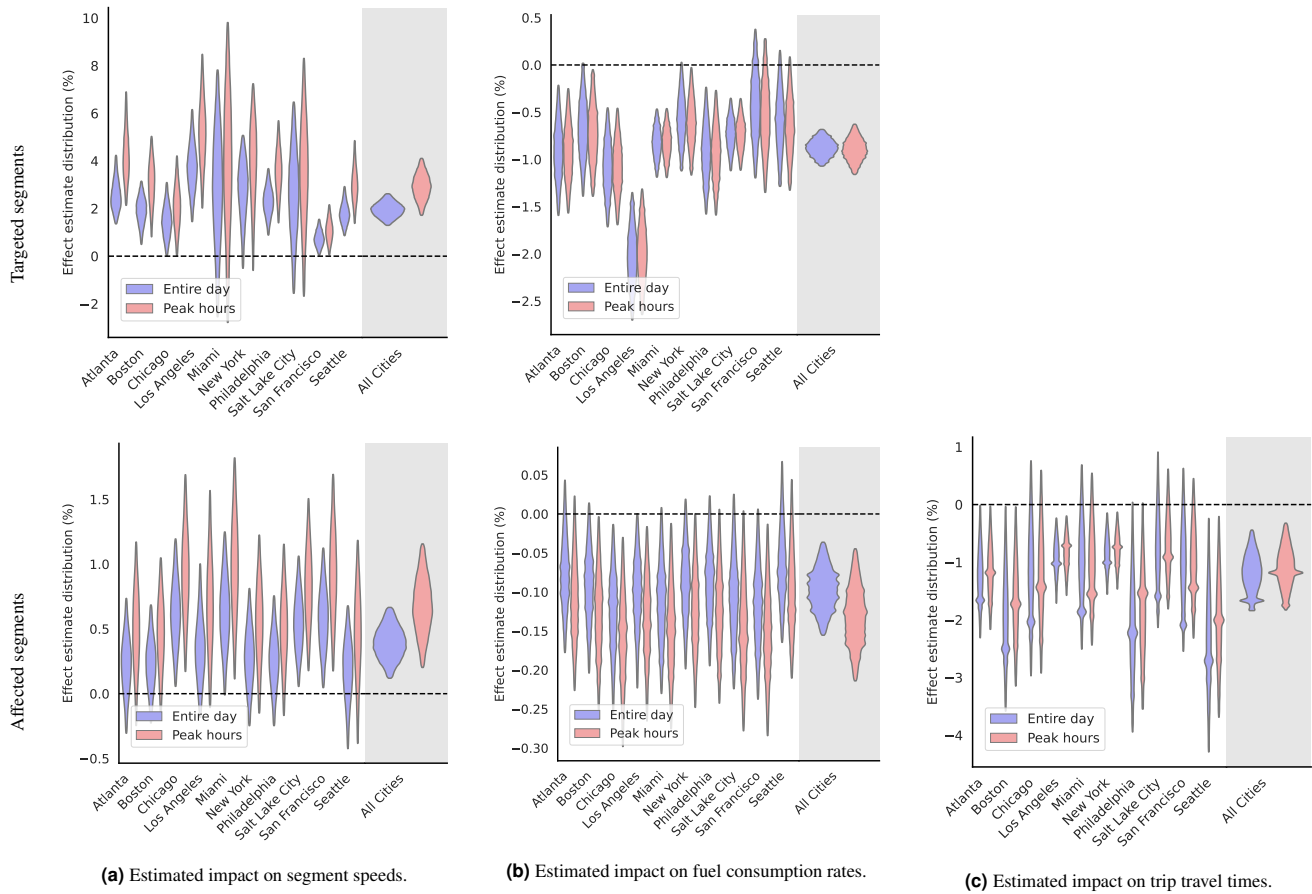
Supplementary Figure 2. MLM results for different outcomes. Statistical significance was determined using a Mixed-Effects Linear Model (MLM). P-values were calculated via two-sided randomization tests (placebo tests), comparing the observed effect size against a distribution of 1,000 random treatment assignments. Findings here are consistent with those from the Bayesian hierarchical modeling approach.



Supplementary Figure 3. Differences in average trip guidance compliance rates between treatment and control periods. Values in brackets denote the standard deviations across both treatment and control intervals. We find no significant difference once alternate trips are assigned.



Supplementary Figure 4. Measured impact of the intervention as a function of observed trip flows.

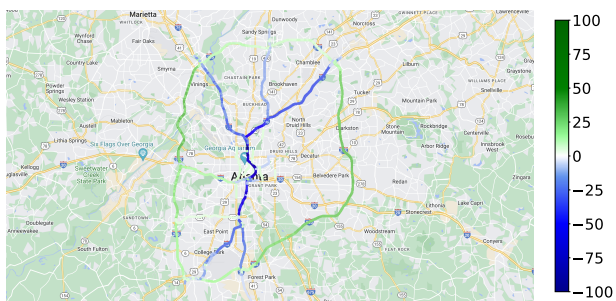


Supplementary Figure 5. Effect estimates similar to the analysis conducted in the main text but including outlier datapoints. Effects are directionally similar but stronger in some instances, possibly as a result of a disproportionate number of high traffic volume events during switchback off intervals.

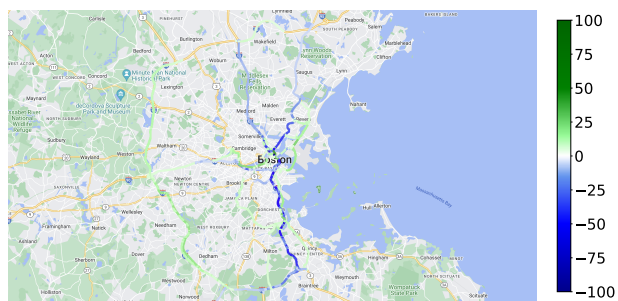
counts. Nevertheless, the distribution of trip counts is similar between switchback on and off intervals, suggesting that our use of switchback off periods as a control group for outcomes is valid. Moreover, the impact of the intervention can be seen visually from this simple aggregation exercise, with an estimated difference between switchback on and off periods of 0.17 km/hr, or a gain of approximately 0.3%.

Effect of the outlier removal process In this subsection, we replicate the findings from the Bayesian hierarchical modeling framework approach while *including* outlier dates to the analysis process. Figure 5 depicts the posterior distributions of average speed gains and fuel consumption rate savings for both targeted and affected segments, as well as the distribution of total travel time reductions. Broadly speaking, we find effects to be directionally similar but stronger in magnitude. In the case of segment speeds, for instance, effect estimates are roughly similar averaged across all cities and hour intervals (roughly a median effect of 0.37% to affected segment speeds when outliers are removed vs. 0.39% when they are included), but notably higher at peak hours (roughly a median effect of 0.49% to affected segment speeds when outliers are removed vs. 0.68% when they are included). Similar trends emerge for fuel consumption rates and total travel times. Relative to one another, insights derived when observing the treatment at a city-by-city basis remain consistent here, i.e. cities in which the treatment appeared most effective when not considering outlier dates continue to be most effective here. We hypothesize that the mismatch in the magnitudes of treatment effects arises from the presence of an imbalanced number of high traffic volume events during control intervals that may confound observed effects. We as such opt to remove them when reporting findings in the main text to provide a more conservative measurement of the treatment effect, but provide unfiltered results here for posterity.

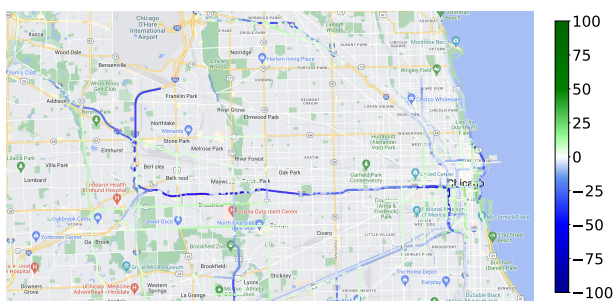
Additional figures For the purpose of completeness, Figures 6 to 9 and Tables 1 to 2 present additional plots analogous to or referenced by other text and figures for each city in this study. The structural hierarchies for the daily and hourly Bayesian models described in the Methods are provided here in Figure 10. These diagrams illustrate the prior distributions and dependencies that facilitate partial pooling across cities and time periods to strengthen subgroup estimates. Additionally, the relationship between vehicle speed and fuel efficiency used for emission assessments is characterized by the data-driven speed-energy consumption curve shown in Figure 11.



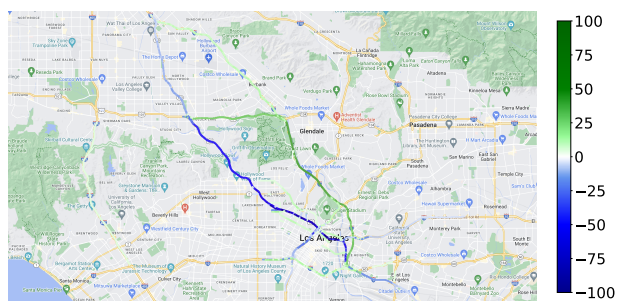
Atlanta



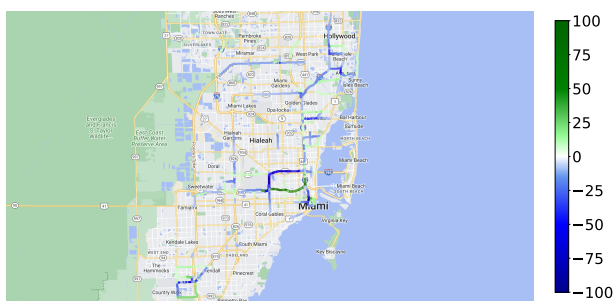
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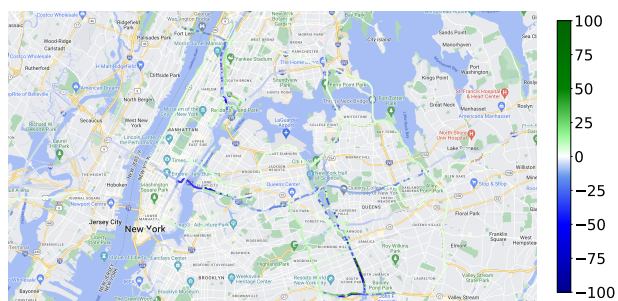
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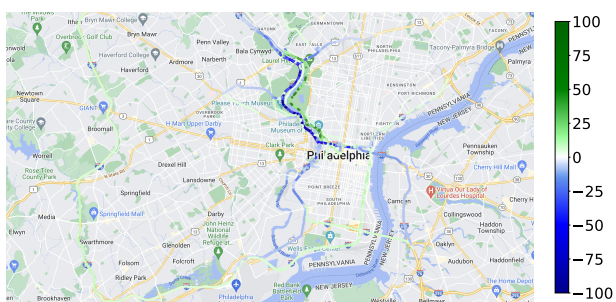
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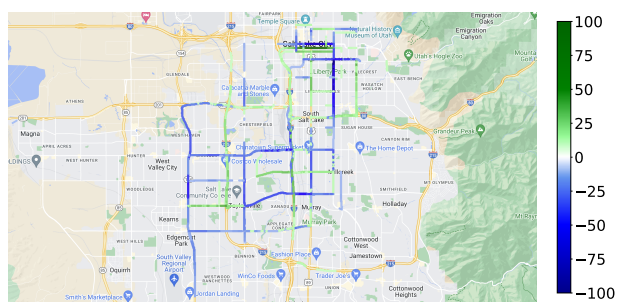
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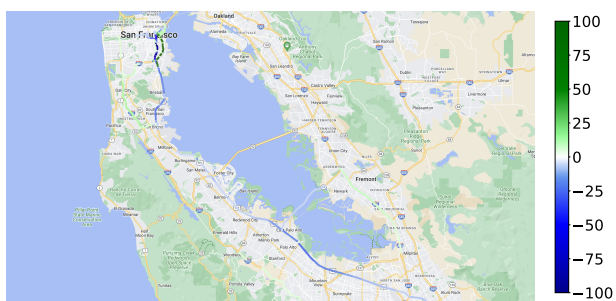
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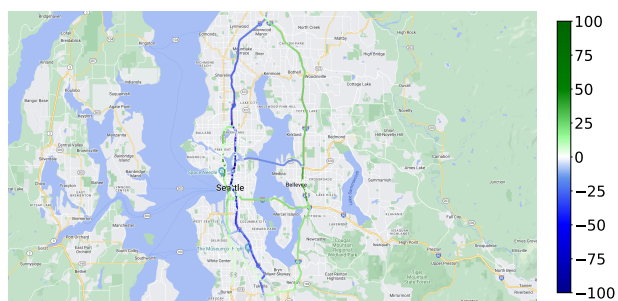
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Salt Lake City

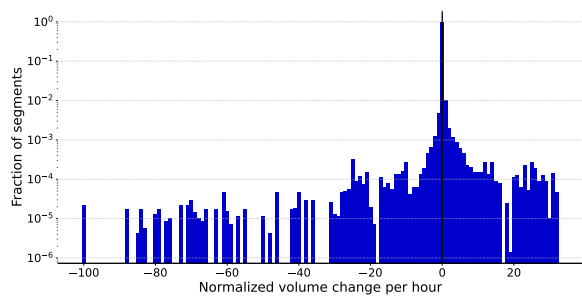


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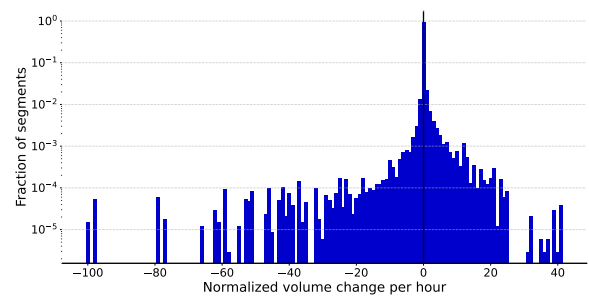


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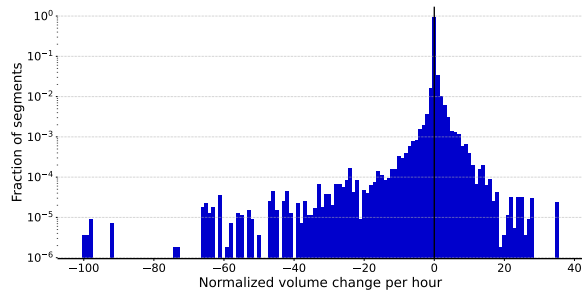
Supplementary Figure 6. Distribution of projected volume changes per segment per hour, normalized to the largest projected volume change per city. Imagery ©2026, Map data ©2026 Google



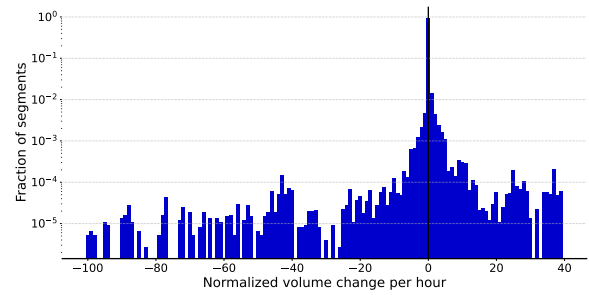
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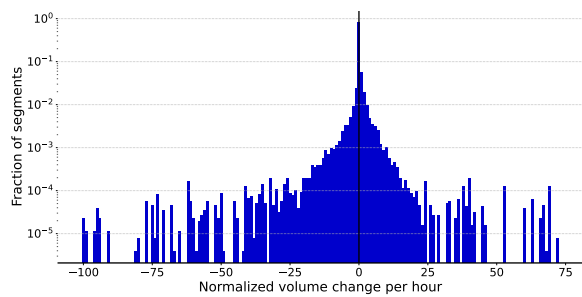
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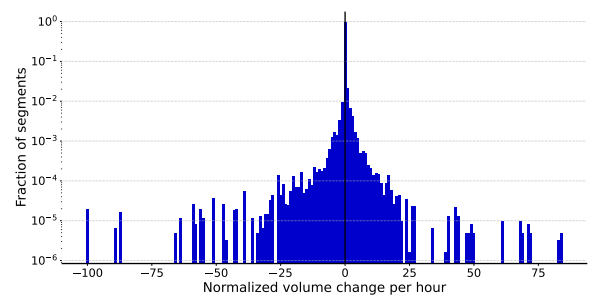
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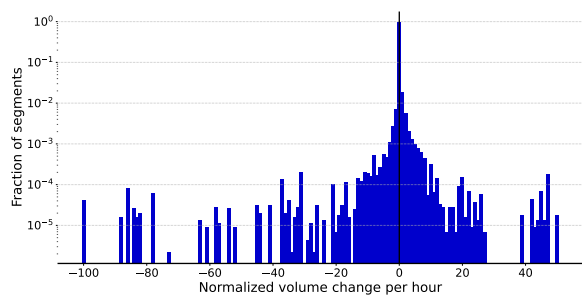
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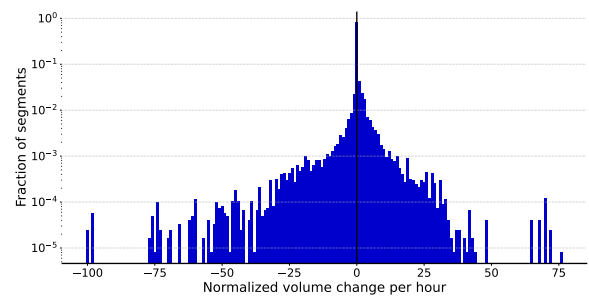
Miami



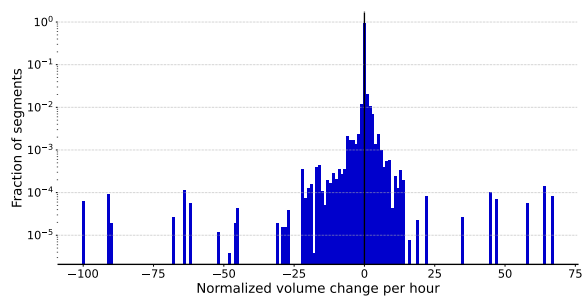
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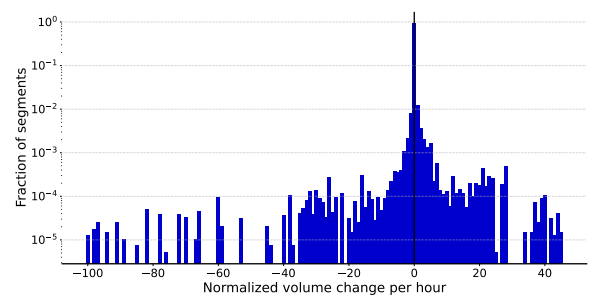
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Salt Lake City

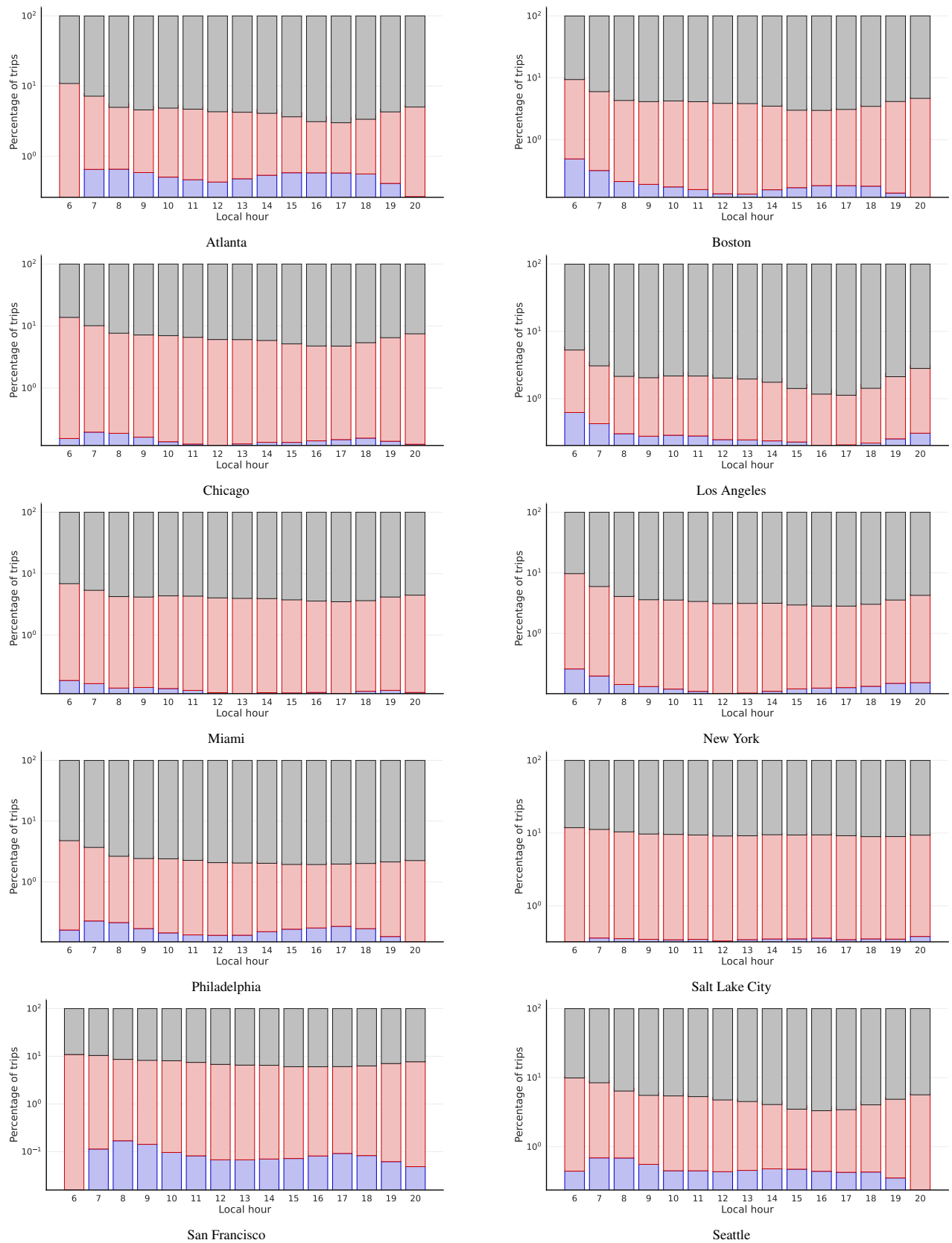


San Francisco

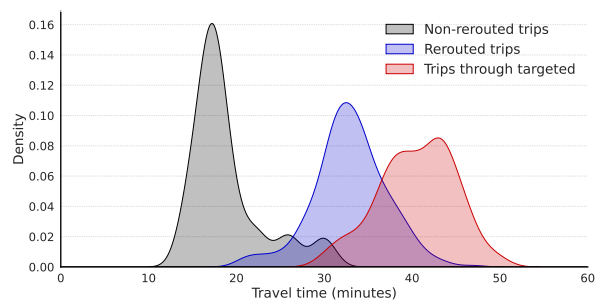


Seattle

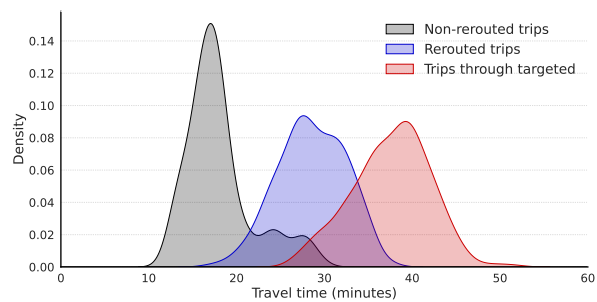
Supplementary Figure 7. Segment counts that experienced certain volumes of redistributed vehicles per hour by city.



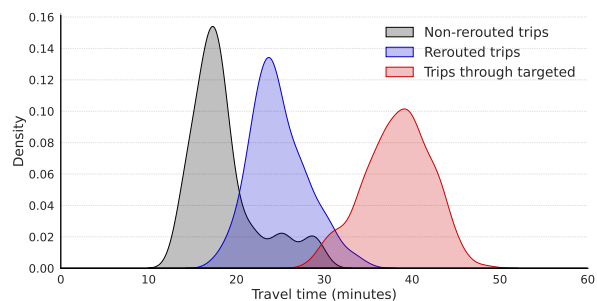
Supplementary Figure 8. Relative number of trips falling under different trip subgroups as a function of time-of-day. Blue corresponds to rerouted trips, red to trips passing through targeted segments, and grey with nonrerouted trips. Note that each subgroup is not mutual exclusion. As such, these figures do not represent the percentage of total trips allocated to each group but rather serve to compare the number of trips assigned alternate routes against other relevant groups.



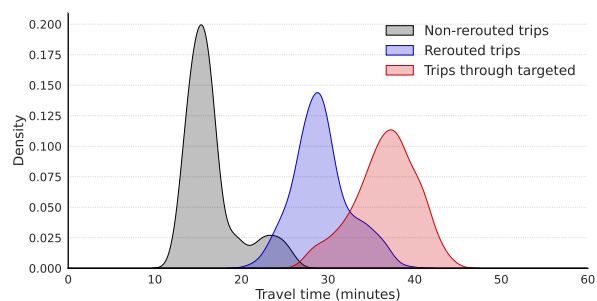
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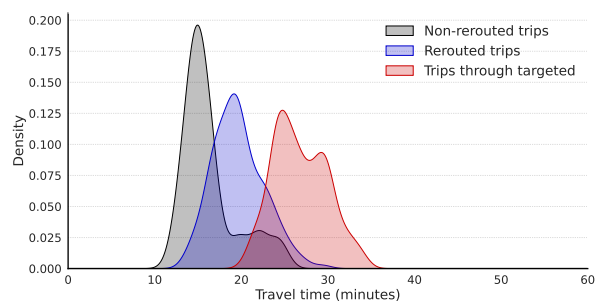
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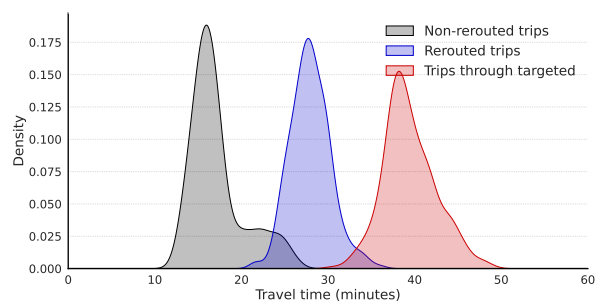
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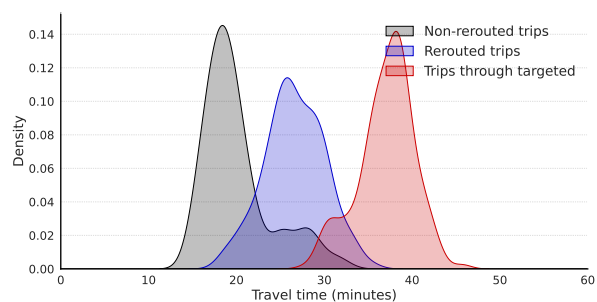
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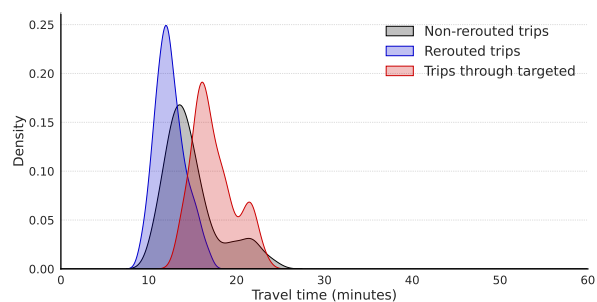
Miami



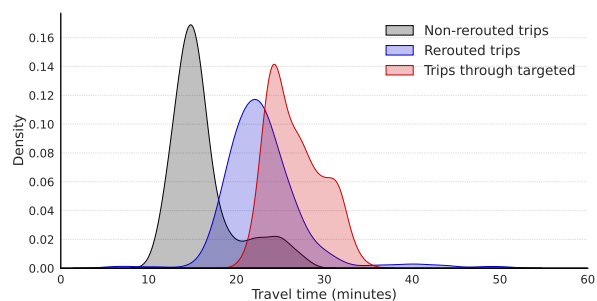
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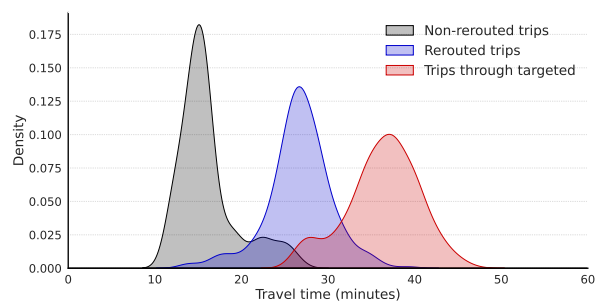
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Salt Lake City



San Francisco



Seattle

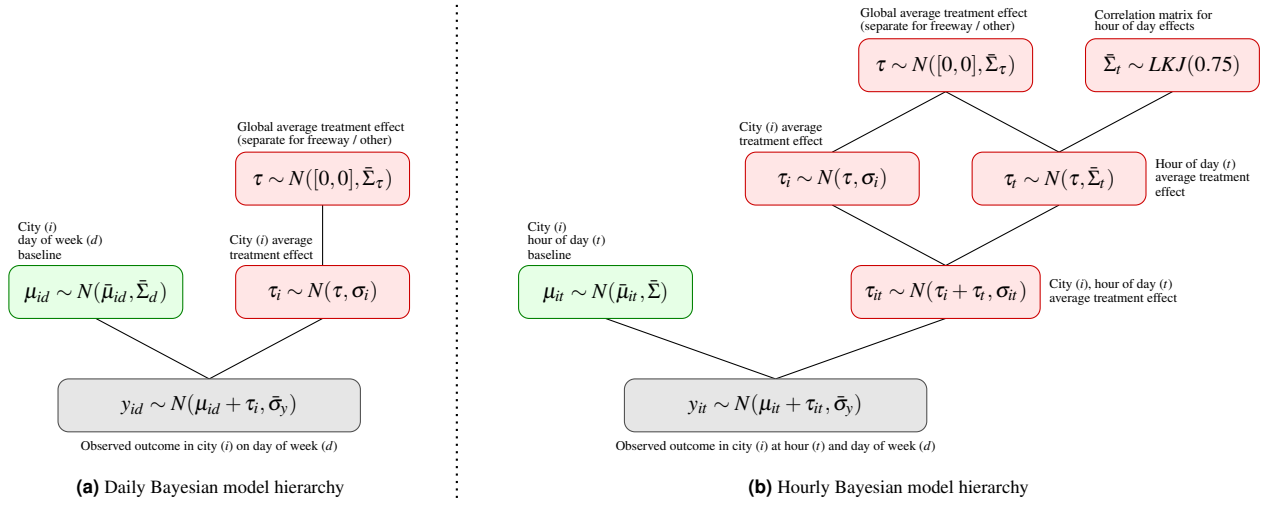
Supplementary Figure 9. Distribution of travel times by different trip subgroups for each target city.

		Speed improvements (km/hr)				Emissions improvements (L/100km)			
		Lower	Middle	Upper	P[pos]	Lower	Middle	Upper	P[neg]
Atlanta	Peak hours	+0.41 (+1.34%)	+1.01 (+3.30%)	+1.81 (+5.88%)	100%	-0.12 (-1.24%)	-0.06 (-0.63%)	0.00 (0.00%)	97.4%
	Entire day	+0.59 (+1.20%)	+1.12 (+2.30%)	+1.87 (+3.83%)	100%	-0.11 (-1.37%)	-0.06 (-0.73%)	-0.01 (-0.05%)	98.3%
Boston	Peak hours	+0.02 (+0.06%)	+0.69 (+2.20%)	+1.25 (+4.00%)	97.8%	-0.10 (-1.13%)	-0.05 (-0.49%)	+0.01 (+0.15%)	93.3%
	Entire day	+0.17 (+0.37%)	+0.79 (+1.69%)	+1.28 (+2.73%)	99.2%	-0.10 (-1.20%)	-0.05 (-0.55%)	+0.01 (+0.10%)	95.3%
Chicago	Peak hours	-0.03 (-0.10%)	+0.54 (+1.61%)	+1.25 (+3.73%)	96.8%	-0.15 (-1.44%)	-0.09 (-0.85%)	-0.03 (-0.27%)	99.7%
	Entire day	+0.15 (+0.34%)	+0.64 (+1.50%)	+1.33 (+3.10%)	99.4%	-0.14 (-1.58%)	-0.09 (-0.97%)	-0.03 (-0.37%)	99.8%
Los Angeles	Peak hours	+0.38 (+1.86%)	+0.92 (+4.56%)	+1.58 (+7.82%)	100%	-0.27 (-2.5%)	-0.20 (-1.89%)	-0.13 (-1.26%)	100%
	Entire day	+0.53 (+1.99%)	+1.01 (+3.80%)	+1.67 (+6.25%)	100%	-0.26 (-2.66%)	-0.20 (-2.04%)	-0.14 (-1.42%)	100%
Miami	Peak hours	-0.47 (-4.21%)	+0.29 (+2.56%)	+0.85 (+7.59%)	78.9%	-0.20 (-1.16%)	-0.14 (-0.82%)	-0.08 (-0.48%)	100%
	Entire day	-0.34 (-2.75%)	+0.39 (+3.08%)	+0.91 (+7.25%)	86.8%	-0.20 (-1.24%)	-0.15 (-0.89%)	-0.09 (-0.55%)	100%
New York	Peak hours	-0.15 (-0.80%)	+0.62 (+3.24%)	+1.21 (+6.36%)	94.5%	-0.12 (-1.05%)	-0.06 (-0.53%)	-0.00 (-0.01%)	97.7%
	Entire day	+0.01 (+0.01%)	+0.72 (+2.91%)	+1.22 (+4.94%)	97.5%	-0.11 (-1.12%)	-0.06 (-0.60%)	-0.01 (-0.05%)	98.5%
Philadelphia	Peak hours	+0.19 (+0.64%)	+0.79 (+2.70%)	+1.40 (+4.78%)	99.5%	-0.13 (-1.31%)	-0.06 (-0.66%)	-0.01 (-0.05%)	98.3%
	Entire day	+0.35 (+0.81%)	+0.89 (+2.07%)	+1.46 (+3.37%)	100%	-0.12 (-1.40%)	-0.07 (-0.76%)	-0.01 (-0.13%)	99.2%
Salt Lake City	Peak hours	-0.39 (-2.83%)	+0.31 (+2.24%)	+0.87 (+6.28%)	82.2%	-0.17 (-1.00%)	-0.10 (-0.62%)	-0.04 (-0.27%)	100%
	Entire day	-0.23 (-1.45%)	+0.41 (+2.55%)	+0.92 (+5.74%)	90.1%	-0.16 (-1.07%)	-0.11 (-0.69%)	-0.05 (-0.34%)	100%
San Francisco	Peak hours	-0.14 (-0.21%)	+0.48 (+0.71%)	+1.11 (+1.65%)	93.8%	-0.09 (-1.13%)	-0.03 (-0.36%)	+0.03 (+0.42%)	81.4%
	Entire day	+0.01 (+0.01%)	+0.58 (+0.66%)	+1.18 (+1.34%)	97.6%	-0.09 (-1.14%)	-0.03 (-0.39%)	+0.03 (+0.34%)	84.7%
Seattle	Peak hours	-0.01 (-0.02%)	+0.71 (+1.8%)	+1.29 (+3.28%)	97.4%	-0.08 (-0.91%)	-0.02 (-0.25%)	+0.04 (+0.43%)	77.4%
	Entire day	+0.12 (+0.19%)	+0.81 (+1.31%)	+1.33 (+2.15%)	98.6%	-0.08 (-1.00%)	-0.02 (-0.31%)	+0.03 (+0.41%)	80.4%
All cities	Peak hours	+0.30 (+1.00%)	+0.63 (+2.13%)	+0.97 (+3.27%)	100%	-0.11 (-0.98%)	-0.08 (-0.74%)	-0.05 (-0.49%)	100%
	Entire day	+0.49 (+1.20%)	+0.73 (+1.77%)	+0.98 (+2.38%)	100%	-0.10 (-1.00%)	-0.08 (-0.82%)	-0.07 (-0.64%)	100%

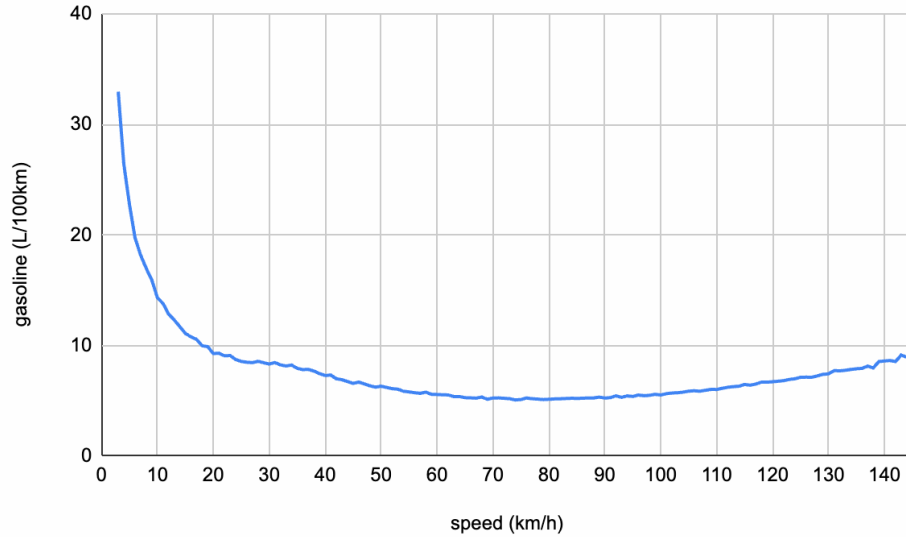
Supplementary Table 1. Estimated speed and emissions gains for directly targeted segments. Percentage improvements are placed in parentheses. Lower, middle, and upper estimates represent the 5th, 50th, and 95th percentile posterior probabilities, respectively. Morning peak intervals are defined as 9:00 – 11:00, and afternoon peaks 16:00 – 18:00. For these sets of segments, we find that the intervention produces positive and significant impacts on both speeds and emissions.

		Speed improvements (km/hr)				Emissions improvements (L/100km)			
		Lower	Middle	Upper	P[pos]	Lower	Middle	Upper	P[neg]
Atlanta	Peak hours	-0.21 (-0.34%)	+0.19 (+0.30%)	+0.59 (+0.95%)	82.9%	-0.01 (-0.17%)	-0.00 (-0.04%)	+0.01 (+0.09%)	74.7%
	Entire day	-0.18 (-0.25%)	+0.15 (+0.21%)	+0.51 (+0.68%)	82.9%	-0.01 (-0.15%)	-0.00 (-0.04%)	+0.01 (+0.08%)	75.0%
Boston	Peak hours	-0.21 (-0.31%)	+0.19 (+0.27%)	+0.59 (+0.86%)	82.9%	-0.02 (-0.20%)	-0.01 (-0.06%)	+0.01 (+0.06%)	83.4%
	Entire day	-0.19 (-0.23%)	+0.16 (+0.20%)	+0.51 (+0.64%)	83.0%	-0.01 (-0.18%)	-0.00 (-0.06%)	+0.00 (+0.05%)	84.8%
Chicago	Peak hours	+0.06 (+0.10%)	+0.48 (+0.77%)	+0.92 (+1.48%)	98.7%	-0.02 (-0.25%)	-0.01 (-0.11%)	+0.00 (+0.02%)	95.1%
	Entire day	+0.07 (+0.10%)	+0.45 (+0.62%)	+0.84 (+1.17%)	98.9%	-0.02 (-0.24%)	-0.01 (-0.11%)	+0.00 (+0.01%)	96.3%
Los Angeles	Peak hours	-0.14 (-0.26%)	+0.24 (+0.45%)	+0.68 (+1.26%)	88.9%	-0.02 (-0.22%)	-0.01 (-0.07%)	+0.00 (+0.05%)	87.9%
	Entire day	-0.12 (-0.17%)	+0.21 (+0.31%)	+0.60 (+0.90%)	89.6%	-0.02 (-0.20%)	-0.01 (-0.07%)	+0.00 (+0.03%)	89.8%
Miami	Peak hours	+0.06 (+0.10%)	+0.46 (+0.83%)	+0.92 (+1.64%)	98.7%	-0.02 (-0.24%)	-0.01 (-0.10%)	+0.00 (+0.03%)	93.3%
	Entire day	+0.06 (+0.09%)	+0.43 (+0.66%)	+0.84 (+1.26%)	98.8%	-0.02 (-0.22%)	-0.01 (-0.10%)	+0.00 (+0.02%)	94.4%
New York	Peak hours	-0.20 (-0.34%)	+0.19 (+0.32%)	+0.59 (+0.99%)	83.5%	-0.02 (-0.19%)	-0.00 (-0.06%)	+0.01 (+0.07%)	80.8%
	Entire day	-0.18 (-0.26%)	+0.16 (+0.23%)	+0.51 (+0.76%)	83.6%	-0.01 (-0.17%)	-0.00 (-0.05%)	+0.01 (+0.06%)	82.0%
Philadelphia	Peak hours	-0.19 (-0.30%)	+0.20 (+0.32%)	+0.60 (+0.95%)	84.7%	-0.02 (-0.19%)	-0.00 (-0.06%)	+0.01 (+0.07%)	81.0%
	Entire day	-0.17 (-0.23%)	+0.17 (+0.23%)	+0.53 (+0.74%)	84.8%	-0.01 (-0.17%)	-0.00 (-0.05%)	+0.00 (+0.06%)	82.6%
Salt Lake City	Peak hours	+0.07 (+0.09%)	+0.48 (+0.68%)	+0.91 (+1.29%)	98.9%	-0.02 (-0.23%)	-0.01 (-0.09%)	+0.00 (+0.05%)	90.7%
	Entire day	+0.07 (+0.09%)	+0.45 (+0.54%)	+0.83 (+1.01%)	99.0%	-0.02 (-0.21%)	-0.01 (-0.09%)	+0.00 (+0.04%)	91.4%
San Francisco	Peak hours	+0.05 (+0.08%)	+0.46 (+0.75%)	+0.89 (+1.45%)	98.4%	-0.02 (-0.24%)	-0.01 (-0.10%)	+0.00 (+0.04%)	92.3%
	Entire day	+0.05 (+0.07%)	+0.43 (+0.57%)	+0.80 (+1.07%)	98.6%	-0.02 (-0.22%)	-0.01 (-0.09%)	+0.00 (+0.03%)	93.4%
Seattle	Peak hours	-0.36 (-0.63%)	+0.13 (+0.22%)	+0.50 (+0.87%)	72.6%	-0.01 (-0.14%)	-0.00 (-0.02%)	+0.01 (+0.13%)	62.5%
	Entire day	-0.35 (-0.51%)	+0.10 (+0.14%)	+0.41 (+0.59%)	70.8%	-0.01 (-0.13%)	-0.00 (-0.02%)	+0.01 (+0.12%)	62.0%
All cities	Peak hours	+0.04 (+0.06%)	+0.30 (+0.49%)	+0.57 (+0.92%)	98.8%	-0.01 (-0.16%)	-0.01 (-0.07%)	+0.00 (+0.01%)	95.1%
	Entire day	+0.08 (+0.12%)	+0.27 (+0.37%)	+0.46 (+0.64%)	99.8%	-0.01 (-0.13%)	-0.01 (-0.07%)	-0.00 (-0.01%)	98.6%

Supplementary Table 2. Estimated speed and emissions gains for all effected segments. Percentage improvements are placed in parentheses. Lower, middle, and upper estimates represent the 5th, 50th, and 95th percentile posterior probabilities, respectively. Morning peak intervals are defined as 9:00 – 11:00, and afternoon peaks 16:00 – 18:00. For these sets of segments, the intervention produces less pronounced, but notably equally significant, impacts on both speeds and emissions as seen for targeted segments.



Supplementary Figure 10. Priors in our Bayesian model hierarchies. Green represents the “baseline” control period outcome hierarchy, and red represents the “treatment effect” hierarchy. Priors on some variance components ($\bar{\Sigma}, \bar{\Sigma}_\tau, \bar{\Sigma}_t, \sigma_{it}, \sigma_i, \bar{\sigma}_y$) omitted for brevity.



Supplementary Figure 11. Data-driven speed-energy consumption curve per vehicle used for fuel emission assessments. This model shows an optimum for medium speeds, in the flat region of this convex fit, a fact well known by practitioners. For data handling and aggregation purposes, we do not consider acceleration as a feature within this model, and as such estimates of fuel emission are derived under the assumption of stationary speeds.