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Urban congestion relief experiments through routing-app interventions

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Traffic congestion remains a persistent challenge for urban mobility, increasing travel delays and elevating CO_2 emissions. The widespread use of smartphones and GPS navigation creates new opportunities to mitigate congestion through routing optimizations in apps, yet real-world evidence for the effectiveness of such interventions is limited. Here we report large-scale empirical experiments evaluating routing-based traffic interventions on ~100 highly congested road segments across 10 major US cities. By rerouting a small share of Google Maps trips from targeted congested highway and arterial segments to less congested alternatives of equivalent road-classes with comparable travel times, we observe a city-average 2% increase in vehicle speeds on the intervened segments, along with improved travel times 0.7% and potential annual reductions exceeding 1,000 tons of CO_2-equivalent emissions per city in the majority of studied locations. These findings provide evidence that marginal routing interventions involving a small proportion of vehicles can measurably enhance overall road network efficiency, offering a practical pathway to easing congestion and advancing urban sustainability.

Transportation systems have played a pivotal role in all urban settings, enabling the movement of goods and people, and enhancing overall rates of productivity and economic growth[1–4]. The prosperity of a city, as such, is intrinsically linked to the health and efficiency of its transportation network. A crucial component allowing the efficient utilization of transportation networks surrounds the choice of routing strategy used to navigate vehicles to their desired destinations. With the proliferation of smartphones and improvements in Global Positioning System (GPS) technology, an increasing proportion of these trips has come to rely on navigation apps such as Google Maps, Apple Maps or Waze to identify optimal routes through a network. Early instantiations of such systems, however, have been largely individualistic, focusing exclusively on minimizing travel times for singular trips. While these systems have evolved to include other metrics, such as fuel consumption[5] and toll costs[6], they remain essentially individualistic: they optimize a specific criterion for either one vehicle or one fleet, without considering the impact on overall traffic or overall emissions[7]. By contrast, many other major traffic networks—such as air traffic and internet traffic—operate through a network aware control system that optimizes network-wide efficiency. Rather than minimize the travel time of a given airplane or byte, the system routes each journey in consideration of its impact on the network as a whole.

A large body of theoretical literature has studied the outcome of greedy versus network-optimized routing across a variety of networks, including the internet[8], supply chains[9], and ground and air transportation[10]. Network-optimized routing can have large advantages over greedy per-vehicle routing[11] in a wide range of settings, including static equilibrium[12], mixtures of system-controlled and greedy agents[13], time-varying settings[14] and dynamic route assignment[15,16]. However, little is known about the improvements that are possible through network-optimized routing in real large-scale road networks.

This article presents the first large-scale empirical evidence that low-cost rerouting for a small proportion of vehicles can measurably improve the overall efficiency of a road network. Within this study, we identify and select road segments in 10 major US cities (~100 per city) depicting historically large levels of demand or an overabundance of congestion during peak demand intervals. Then, over a 6-month period, our experiment dispersed traffic away from these segments by

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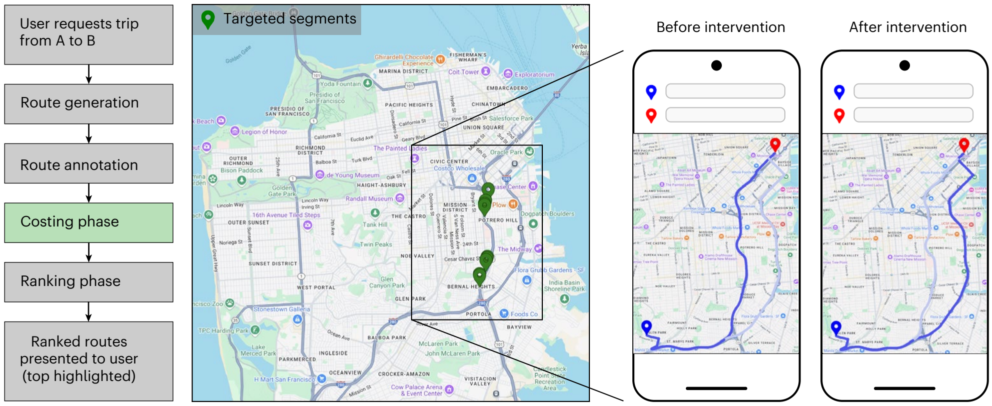

Fig. 1 | In this study, we explore methods for reducing traffic congestion by navigating trips away from heavily congested segments. Left: our method impacts the costing phase of typical routing services, as outlined within the Methods. Earlier factors, namely the selection of feasible paths, are not affected here. Middle: within the costing phase, we assign additional costs to feasible trips passing through preselected segments depicting disproportionate levels of demand. Right: the added penalties reroute trips with similarly costing alternative paths away from these segments, thereby reducing the flow of traffic that would have otherwise been experienced within them. Imagery ©2026 Google Maps; map data ©2026 Google.

altering the costs assigned to suggested routes passing through them. During designated 'treatment' periods, this modification algorithmically allowed trips with marginally similar costs to prefer paths not containing the set of 'targeted' segments, thereby reducing the volume of traffic that passed through them. Our routing intervention bounded trip-level costs with respect to the fastest viable path, ensuring that rerouted vehicles were assigned routes with travel times that were comparable to those of the original path (for instance, diverted routes were required to be within a few percentage points of the fastest baseline travel time). In total, under 2% of observed trips directly experienced altered routing recommendations as a result of the intervention. An outline of this process is depicted in Fig. 1. A more detailed description of the algorithmic modifications and set of targeted segments (see Table 1 for selected segments) can be found in the Methods.

Assessing the impact of this intervention required three key components. First, we relied on high-volume aggregated and anonymized metrics from Google Maps to produce high-quality assessments of time-varying segment speeds. Second, we used a switchback (also known as crossover) experimental design that alternated the treatment status of all users in a given geography over time. Switchback designs are commonly used in medical studies and have recently been adopted by ride-hailing platforms such as Uber and Lyft[17–20]. Third, we analyzed the experimental data using both Bayesian and frequentist approaches to maximize the statistical power of our findings given inherent day-to-day variance while ensuring the robustness of our results. Results from the frequentist approach can be found in the Supplementary Information.

The results of our experiment were positive and substantial. We find improvements to driving speeds on both the set of targeted high-congestion segments and the much larger set of 'affected' segments: all segments that were impacted by the intervention, including those to which traffic was redirected either away from or onto. The set of affected segments covers about 80% of traffic in each city. Changes in individual trips are small but add up to statistically significant gains in network travel times, validated by multiple statistical approaches. To quantify the environmental impact of these network improvements, we estimate potential emission savings attained from observed improvements in network driving speeds. We find that improvements on this style could save hundreds to thousands of tons of CO_2 emissions per city per year.

Results

Data collection

For this study, we use two classes of aggregated and anonymized outcome statistics: (1) segment-level outcomes, aggregated in time and space across road segments throughout each city; and (2) trip-level outcomes, aggregated across end-to-end trips. Each outcome is computed at hourly time intervals and on weekdays between 7:00 and 20:00, inclusive.

Segment-level outcomes. We focus our assessment of segment-level outcomes on two groups of segments: (1) segments that were directly targeted by our intervention, X_{targeted}; and (2) segments that may have been affected by the intervention, X_{affected}. The only segments included in X_{targeted} are those that were directly used for determining whether trips would be rerouted or not. The set of 'affected' segments X_{affected} includes the broader set of all segments that were impacted by the treatment, including segments on routes that vehicles were diverted from (whether or not the particular segment was targeted) and segments on routes that rerouted trips were diverted to as a result of the treatment. Figure 1 (right) demonstrates the segments from one such trip. X_{targeted} consists of the small number of green pins, while X_{affected} consists of all of the segments in blue—from both the 'before' and the 'after' intervention routes. The two routes capture potentially converse effects. Segments that trips are routed away from may experience a reduction in traffic flows as a result of the treatment and, as such, may see improvements to road efficiency metrics. Segments that trips are routed onto could experience increases to traffic flows that may affect them negatively. Considering both groups of segments together allows us to quantify the net effect of the intervention.

For each segment $i \in (X_{\text{targeted}} \cup X_{\text{affected}})$ and hour t, we use the total travel time $\text{TTT}^i(t)$, total distance traveled $\text{TDT}^i(t)$ and estimated fuel consumption rate $f^i(t)$ (in liters per 100 km) of trips driving along i during t. We then estimate the average observed speed in a given city $\bar{v}(t) = \sum_{i\in X}\text{TDT}^i(t) \,/\, \sum_{i\in X}\text{TTT}^i(t)$ as the total distance traveled divided by the total time spent within a segment set X (either X_{targeted} or X_{affected}) and compute a similar estimate for fuel consumption rates weighted by total distance traveled $\bar{e}(t) = \sum_{i\in X}(f^i(t) \times \text{TDT}^i(t)) \,/\, \sum_{i\in X}\text{TDT}^i(t)$. This yields a dataset comprised of hourly observations of average segment-level speeds and fuel consumption rates by group for each city. Under the switchback design, all segments switch between treatment and control status on a daily basis so that hourly outcomes on adjacent days can be directly compared for targeted and affected segment groups.

Trip-level outcomes. We augment our segment-level analysis with two trip-level outcomes: (1) trip travel times and (2) user experience metrics. While segment-level outcomes characterize the road conditions for an average traversal of the road network, trip-level outcomes

Table 1 | Employed segment selection approach within each city in this study

City	Number of segments	Congestion criteria	Road class
Atlanta	106	Density at peak demand	Freeway segments
Boston	108	Density at peak demand	Freeway segments
Chicago	81	Presence of bottlenecks	Mixture of freeways and arterials
Los Angeles	120	Density at peak demand	Freeway segments
Miami	100	Density at peak demand	Arterial segments
New York	103	Density at peak demand	Freeway segments
Philadelphia	101	Density at peak demand	Freeway segments
Salt Lake City	94	Density at peak demand	Arterial segments
San Francisco	102	Presence of bottlenecks	Segments along US-101
Seattle	97	Density at peak demand	Segments along Interstate I-5

account for compositional differences between segments that might be traversed in different kinds of trips. Our initial analysis focused only on segment-level outcomes and used a full 6 months of data. We added a trip-level analysis to ascertain our results on network effects after the initial analysis was done. Due to data retention limitations, we were only able to use the final 2 months of data for this second analysis. We compute hourly averages for each outcome at the city level, weighting each trip uniformly.

Targeted segments—large speed increase and emissions decrease

We begin by presenting results on the impact of the intervention on segments directly targeted by the study. Figure 2a,b (top) depicts the posterior distribution of average speed gains and fuel consumption savings via a hierarchical Bayesian modeling approach described in the Methods. We see marked improvements to both driving speeds and fuel consumption rates across all cities and times of day. Averaged across cities, we observe a median increase of around 2% in driving speeds on targeted segments, corresponding to a median decrease of 0.5–1.0% in fuel consumption rates. To maximize insights from this experiment, different cities were allocated different types of congested segments for targeting. Some cities had only highway segments, while others had only congested freeways, arterials or a mix thereof. The impact of the intervention was particularly pronounced in cities where freeway segments were targeted. This is the case in Atlanta and Los Angeles, for instance, for which the median speed effect was 3.30% and 4.56%, respectively.

All segments—speed increase and emissions decrease

As expected, removing traffic from targeted segments improves the performance of those segments. We now explore whether these improvements are offset by decreased performance on the other segments, to which we had dispersed traffic. Figure 2a,b (bottom) depicts the posterior distributions of average speed gains and fuel consumption rate savings, respectively, on all affected segments for each of our cities. As the figures show, the set of affected segments saw net improvements to driving speeds and modeled fuel consumption rates, with a probability of 99.8% and 98.6%, respectively, of a positive outcome for aggregate effects across cities. Averaged across all cities and hours of the day, driving speeds increased by around 0.35% on median. Focusing on peak hours only, the median effect on driving speeds was stronger at around 0.50%. Emissions savings across all affected segments were also generally positive, but relatively more diluted. Aggregating across all trips and segments, and extrapolating proportionally to the yearly level, the median estimated savings are equivalent to around 1,000+ tons of CO_2-equivalent (CO_2e) emissions per year. Measurements for each city are provided in Table 2.

Full network impact on total travel times

Due to variation in routes taken at different times, not all segments may have data points for every time interval. As such, outcomes derived from aggregated segment speeds may not capture the same set of segments in each time interval. To address this, we also consider travel times for trips passing through any of the affected segments. Aggregating to the trip level, Fig. 2c depicts the posterior distributions of total travel time savings for trips that passed through affected segments. While the effects vary substantially across cities—reflecting differences in trip composition in each case—we observe qualitatively similar outcomes in total trip travel times to those seen in driving speeds on affected segments. Averaged across cities, we observe a median aggregate drop in total travel times of 0.69%, and drops in the vicinity of 0.5% to 1.0% in each city. This result serves to reinforce the findings from previous sections: whether we look at aggregate speed changes on all affected segments (as in the previous section) or aggregate travel times for all observed trips that passed through any of the affected segments (as in this one), we obtain a qualitatively similar conclusion regarding the efficacy of our intervention.

Mechanisms—efficient traffic dispersion

Network efficiency may improve when a fraction of trips from overutilized segments are shifted to close substitutes that are underutilized. In this subsection, we show that our intervention generally used favorable reroutings in this vein. Figure 3 depicts the average expected change in traffic flows as a result of the intervention. As the figure suggests, our intervention generally moved flows from concentrated central roads to a larger and more dispersed set of nearby roads. These examples center on I-85 in Atlanta, but we see similar patterns, for instance, along Interstate I-5 in Seattle and I-290 in Chicago. In each case, the segments for which flows decreased the most tended to be concentrated near targeted segments, and often extended along the primary highways within which the intervention was employed. By contrast, the segments for which flows increased the most tended to be more geographically diffuse and received fewer vehicles on average—thereby not impacting those segments negatively and resulting in a net positive outcome.

This disparity is largely mechanical. While penalties are assigned at fixed, high-demand segments, the origins and destinations for vehicles passing through these segments vary significantly. As such, the optimal alternate paths for these different trips pass through a wider variety of segments. In the case of Atlanta, as depicted in the top right of Fig. 3, trips that may once have passed through Interstate I-5 are sometimes sent east through I-450, and either via I-90 or other connections further south—or are sent west and spread across various highways and arterials within the city, depending on the destination.

To see this type of traffic dispersion more systematically across segments, Fig. 3 (bottom) plots the histogram of average volume changes across segments in Atlanta. As the figure shows, traffic is typically diffused from a small number of segments and spread across many other segments, each of which receives fewer additional vehicles on average. This supports the thesis of our intervention: it demonstrates that low-cost penalties applied to highly congested road networks help to homogenize traffic throughout the network and limit the negative effects experienced on segments receiving higher traffic flows. Similar histograms for all of the cities in our study are provided in Supplementary Fig. 7.

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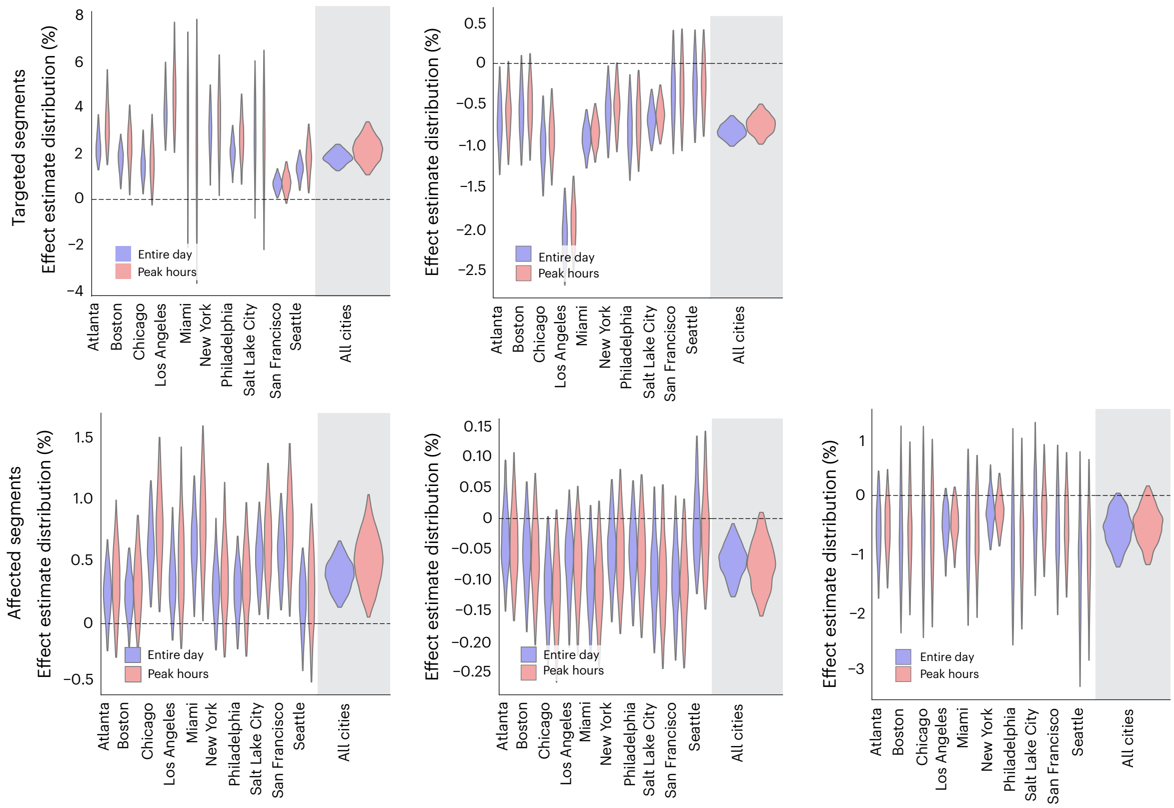

Fig. 2 | Effect estimate distributions for different data sources. a,**b**, We see notable improvements to both targeted and affected segment speeds (**a**) and fuel consumption rates (**b**). Outcomes when computed across all affected segments are understandably more diffuse but still positive, particularly during peaks hours. Numerical values associated with these distributions may be found in Supplementary Tables 1 and 2. **c**, Effects are also present within total travel times.

Table 2 | Predicted yearly CO_2e emissions savings for each city in the study, in tons per year

	Atlanta	Boston	Chicago	Los Angeles	Miami
Savings (5%)	−7,537.42	−4,979.90	−9,547.86	−13,956.27	−4,124.46
Savings (50%)	−1,991.30	−1,499.16	−4,296.54	−4,511.44	−1,816.99
Savings (95%)	+4,715.98	+1,410.97	+656.42	+2,369.32	+484.90
	New York	**Philadelphia**	**Salt Lake City**	**San Francisco**	**Seattle**
Savings (5%)	−8,587.07	−4,453.31	−1,577.04	−5,247.74	−3,458.31
Savings (50%)	−2,514.42	−1,369.08	−657.72	−2,285.15	−503.77
Savings (95%)	+3,820.47	+1,521.76	+414.81	+992.30	+3,921.23

Emissions by routed trips here are extrapolated from data collected on affected segments for weekdays between the hours of 7:00 to 20:00. Total emissions are then estimated by assuming a fixed penetration rate. Finally, savings are estimated by multiplying these terms by predicted savings from the Bayesian model for different percentiles (Fig. 2b).

Discussion

Our approach to network-aware routing presents promising results for improving network efficiency in ten major US cities. The results from our experiment document sizable improvements to travel time, segment speeds and fuel consumption rates from targeting specific segments to divert traffic away from especially congested areas. This demonstrates that even marginal interventions could yield significant benefits to aggregate traffic conditions.

The Dynamic Traffic Assignment literature is extensively studied[15] and has been the subject of rich and ongoing work[14,16]. Dynamic Traffic Assignment framework implementations dynamically adjust flows at each time step to incorporate updated travel time information on corresponding paths. Our approach differs from those implementations as we updated the segment cost based on historical congestion patterns. However, this work contributes to the existing literature by providing empirical evidence that incorporating marginal cost can positively affect overall traffic conditions.

Our primary statistical analysis uses a hierarchical Bayesian model. Our 'Additional results' section within the Supplementary Information shows similar results based on a standard mixed linear model. We also report a range of additional measures such as effects on trip flows and trip guidance compliance. In each case, we find evidence supporting our main results.

The impact analysis in this study is based on aggregated and anonymized trip and traffic statistics from Google mobility data. Incorporating additional traffic measurement sources in the future would offer a more comprehensive perspective. Our study leaves several open questions. First, our findings show that a relatively simple penalty and rerouting algorithm can provide substantive network-wide benefits, but they do not provide an estimate of the additional improvements that may be

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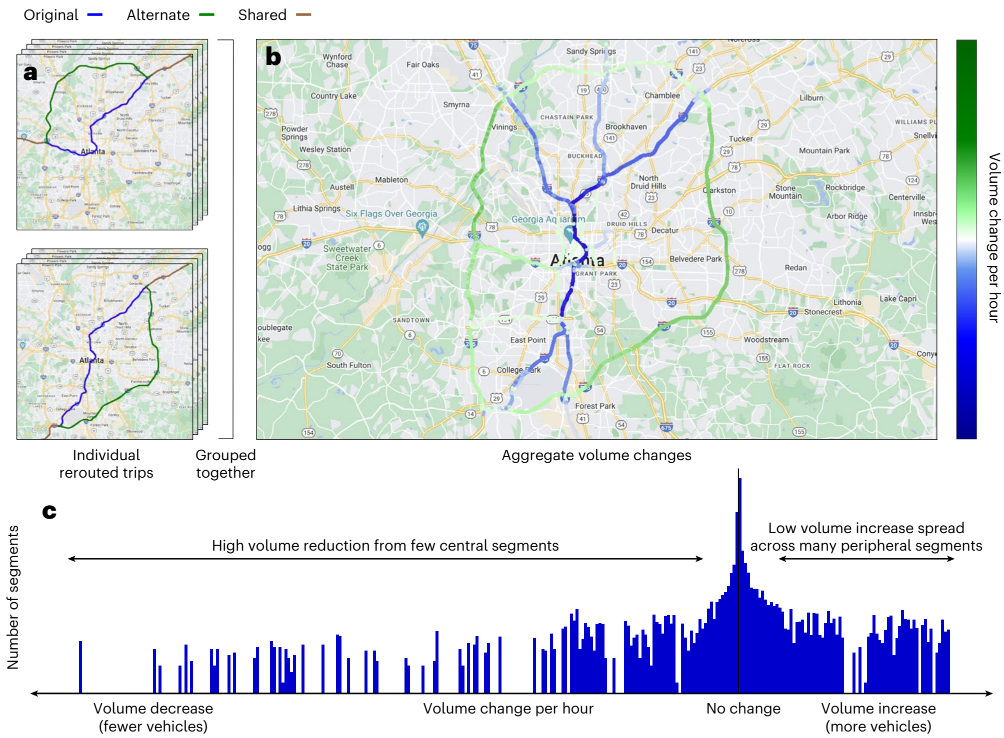

Fig. 3 | The dispersion of traffic across segments in Atlanta induced by the treatment. For each trip rerouted by our treatment, we consider the 'Original' (unaltered) path it would have been assigned absent the treatment and the 'Alternate' (rerouted) path that it was ultimately assigned. **a**, These routes may have substantial overlap (in brown) but typically differ in that the Original (blue) path goes through central highly congested roads, whereas the Alternate (green) uses a less central path. To summarize the effects across all these trips, we compare the total number of vehicles on each segment that would result if all trips were sent through the Original path, and separately, if all trips were sent through the Alternate path. **b**, The net increase (green) or decrease (blue) of volumes on segments under the Alternate (rerouted) paths relative to the Original paths on a map. **c**, A histogram of net volume changes on individual segments. As the map shows, the net effect of the treatment was to divert volumes away from the central roads bisecting Atlanta and onto the major roads outside the center. The histogram shows that this effect dispersed vehicles from concentrating on a smaller number of high-volume segments to a larger number of peripheral segments that each received lower volume increases. Imagery ©2026 Google Maps; map data ©2026 Google.

possible under optimal dynamically computed rerouting penalties. While this approach yielded positive results, future research should explore fully optimal strategies that dynamically account for complex feedback loops, potentially yielding even greater network efficiencies. Second, while our analysis shows an instantaneous improvement in network efficiency, an induced demand response over a longer time horizon and/or expanded treatment region could mitigate the travel time improvements of our intervention. An induced demand response would entail that additional drivers who had previously been deterred from using the targeted road segments by high travel times would switch to these segments upon learning that the travel times have lowered. While this is an important area for future work, our intervention behaves quite differently from the highly visible supply changes that are typically studied in the literature around induced demand for road networks[21]. The network-wide benefits of our intervention are substantial in aggregate, but individuals are unlikely to perceive the difference, as the average savings are about 0.25% of an average affected trip length and 1/40th of the standard deviation of day-to-day trip time variability. Nonetheless, understanding the equilibrium response to a broader network-aware routing approach requires further study and remains open for future work.

Our study demonstrates that it is possible to improve network-wide performance by a statistically discernible level while maintaining strict safeguards against significant impact to rerouted users. In this way, it also provides evidence for the efficacy of rigorous experiment-based traffic management. As smart cities technology advances, the experimental pathway demonstrated here—leveraging connectivity to actuate and measure system-level changes—can extend beyond routing. This work establishes a foundation for future researchers to empirically validating broader network optimization strategies, such as dynamic signal control and real-time feedback integration, within complex urban environments.

Methods

Experimental setup

In this section, we provide a detailed description of the experimental setup of the intervention and the statistical approaches used for impact analysis.

Processes encompassing typical routing apps. Routing applications have become the primary method through which individuals plan trips. These systems, in practice, follow similar general processes from initial request to path assignment. We present a simplified yet generic workflow of how these applications work to provide context on where our intervention is positioned. The process diagram of this workflow is depicted in Fig. 1 (left). These workflows begin with a user requesting a trip between a given origin and destination. Once requested, the underlying routing service then runs the following steps:

(1) Route generation: First, the routing service identifies a set of feasible routes $\mathcal{P}$ in the network between a trip's origin and destination. This step typically aims to find the shortest paths under the current traffic conditions while covering a variety of different paths, thereby ensuring a certain degree of diversity when selecting routes further downstream.
(2) Route annotation: Next, the service annotates each route with information needed to make personalized recommendations. Examples of annotations include the predicted travel time for a given route, the amount of fuel you expect to use while traversing it,

and other special requirements, such as whether the route passes through a toll, highway or ferry, and the difficulty of maneuvers through the turns on this route.

(3) Costing and ranking: Once annotations are provided for each route, a cost is assigned to each route that takes into account both the travel time as well as any customizations. Mathematically put, let $f(\mathcal{P}_i)$ and $c(\mathcal{P}_i)$ be the estimated travel time and auxiliary costs assigned to path $\mathcal{P}_i \in \mathcal{P}$. The auxiliary cost captures characteristics of the route other than travel time and is generally a function of user preference. For instance, in the case of toll-free routing[6], an additional fixed travel time cost may be assigned to paths through tolls. Then the cost C_i assigned to route $\mathcal{P}_i$ is

$$C_i = f(\mathcal{P}_i) + c(\mathcal{P}_i). \quad (1)$$

The routing service then ranks each route in cost-increasing order and assigns the route with the least cost as the reference.

Finally, once the above processes are complete, the routing recommends the optimal route to the user, highlighting the reference route while providing alternatives for the user's discretion.

Externality cost assignment for targeted segments. In this article, we explore methods for inducing network-aware routing through the costing and ranking phase of the routing service, as outlined in the previous section. To do so, we identify segments with historically high levels of congestion, then attempt to divert subsets of vehicles away from these segments by assigning additional costs to trips passing through them. Returning to the notation introduced in the previous section, consider a path $\mathcal{P}_i \in \mathcal{P}$ within the set of viable paths $\mathcal{P}$ assigned during the route generation phase, and let X_{targeted} be the set of segments targeted by the intervention. For each segment $x \in \mathcal{P}_i$ contained within the set X_{targeted}, we assign a fixed externality cost ΔT if the speed of the segment at time t is below what is considered a threshold for congestion, $v_{\text{congested}}(x)$. The congested speed here is assigned as a fixed fraction of the free-flow speed of the segment. Conditioning this cost on congested speeds ensures the treatment is inactive during free-flow conditions, during which the introduction of additional vehicles should play no detrimental role to travel times. In its unadulterated form, this results in a new cost C_i' to the path $\mathcal{P}_i$ of the form

$$C_i' = f(\mathcal{P}_i) + c(\mathcal{P}_i) + \sum_{x \in X_{\text{targeted}} \cap \mathcal{P}_i} c_{\text{ext}}(x, t), \quad (2)$$

where

$$c_{\text{ext}}(x, t) = \begin{cases} \Delta T & v(x, t) < v_{\text{congested}}(x), \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

and $v(x, t)$ is the average speed of vehicles passing through segment x at time t. The added externality cost subsequently adjusts the rankings of trips for which these additions exceed a certain threshold, thereby reducing the flow of traffic on targeted segments. For costs based purely on travel time (that is, $c(\mathcal{P}_i) = 0\, \forall \mathcal{P}_i \in \mathcal{P}$), this is equivalent to upranking routes that are less than a multiple of ΔT longer in terms of predicted travel time, but with equivalently fewer segments within the targeted set. For multi-objective cost structures, however, as is the case here, this comparison becomes somewhat more complex.

The above cost C_i', if left unfiltered, may result in instances whereby assigned alternate routes are unreasonably long, particularly when the only desirable paths assigned to a given trip pass through multiple targeted segments. This is a common theme within the field of system optimal routing, whereby some users may experience substantially higher travel times in a system optimum assignment if the assignment is left unconstrained[22,23]. To avoid rerouting trips in these instances, we apply a capping term $c_{\max}(\mathcal{P})$, which limits the magnitude of the added cost. This capping term aims to capture indifference to marginal properties of a given path $\mathcal{P}_i$ in relation to the full set $\mathcal{P}$, taking into account for instance how much slower a given path is compared with the fastest path in the set. The final augmented cost C_i' is

$$C_i' = f(\mathcal{P}_i) + c(\mathcal{P}_i) + \min\left(\sum_{x \in X_{\text{targeted}} \cap \mathcal{P}_i} c_{\text{ext}}(x, t),\; c_{\max}(\mathcal{P}) \right). \quad (4)$$

For this study, we use a capping term of that caps the travel time cost for the assigned trip within a few percentage points of the best alternate when the auxiliary penalty is not assigned. In practice, we find that, for rerouted trips, this corresponds on average to a 30-s slower alternative in terms of projected travel times.

Segment selection. For each city in this study, we select approximately 100 road segments to be directly impacted by the intervention. Segments here are selected primarily in accordance with measurable and readily visible metrics of excess congestion or disproportionate levels of demand. Two metrics were used to locate these segments:

(1) Density at peak demand: In this first metric, we identify segments in each city with the highest vehicle densities at peak demand intervals. We calculate this by considering the top nth percentile density from the aggregated density list for each segment, where n is set to 75% for this study. This metric allows us to focus on areas with the most significant congestion during peak times. Note that densities here are approximated from observations within our data collection pipeline and, as such, are subject to estimation errors and may underestimate the densities of segments through paths that are less likely to require routing-based guidance. Future studies could improve upon this by utilizing more robust measurement tools, for example, by relying on loop detectors or traffic monitoring cameras.

(2) Presence of bottlenecks: In this second metric, we identify segments that act as bottlenecks, or local restrictions to traffic flow or capacity. Bottleneck segments are identified through common methods within the literature, in particular by comparing the speeds of segments to those directly downstream of them[24]. Segments are then either randomly selected from the list of bottleneck segments (as is the case in Chicago) or selected to coincide with a specific highway (as is the case in San Francisco).

In addition to levels of demand or congestion, segments were selected across different cities in accordance with their road class, that is, whether a segment is a freeway, arterial or part of a specific highway. Different cities were assigned different road classes to quantify the importance of penalizing freeways versus arterials, and so on. Table 1 depicts the segment selection approach, road class and number of segments selected for each city.

Statistical analysis tools

In this section, we describe the statistical analysis tools used to analyze the data and provide robustness checks to the findings. We also describe the data filtering process employed, particularly outlier removal.

Hierarchical Bayesian outcome modeling framework. To accommodate the nonrandom treatment assignment in our experiment, we opt to conduct our main analyses using a hierarchical Bayesian outcome modeling framework[25,26]. Partial pooling models provide us with a flexible way to allow effects to be similar at the city level and the hourly level without imposing hard constraints on how the effects can be related. We allow information to be shared between cities and time periods, so that our estimates on the effect on one particular city or time can be strengthened by concurrent effects found for other subgroups. Another advantage of a Bayesian approach is that it facilitates transparent probabilistic statements about effect sizes, which can be used to express the level of confidence regarding each result to policymakers. Finally, the Bayesian approach allows us to mitigate multiple hypothesis testing issues due to the numerous hypothesis tests regarding treatment effects by hour, by day and by city.

We construct a hierarchical model that defines priors on city-level hour-of-day baselines at the 'top' level of the hierarchy for control period outcomes. In addition, for the treatment effect, we construct a hierarchy starting with a global effect on the uppermost level that has a Gaussian prior with a zero mean. We impose a prior that lets freeway-targeted cities have a different global effect from other cities; hence, the global effect baseline is two-dimensional. For the average effects at the city level and average effects for each hour of day, we impose priors that are Gaussian with means coming from the global effect on the highest level, either from the freeway or non-freeway city global baseline, depending on the status of each city. We also allow the hourly effects to be correlated and define a diffuse prior on the correlation matrix between them. The full hierarchy is shown in Supplementary Fig. 10 (right). When reporting effect estimates on speeds or emissions, we report posterior probability distributions of τ_{it}, averaged over different hours based on the time period of interest (for example, morning peak hours or evening peak hours).

For the experimental analysis of travel times, we use observations over a shorter time period. Given the shorter horizon, estimating hourly treatment effects and baselines becomes more challenging. Therefore, we opt to use a 'day of week'-based hierarchy, aggregating observations on a daily basis. The model structure is shown in Supplementary Fig. 10 (left). When reporting effect estimates on travel times, we report posterior probability distributions of τ_i for each city.

Outlier detection and removal. A particular challenge that arises when evaluating the efficacy of the intervention is that of days when road usage is particularly low. In these relatively infrequent cases, measures of network health—for example, observed speeds and emissions—can improve temporarily and sharply due to factors outside the control of the intervention. If observed disproportionately in either treatment or control intervals, this could result in a skewed interpretation of the efficiency of the intervention. To address this challenge, we conduct a simple outlier detection procedure, searching for time intervals in which traffic density falls significantly outside of the scope of values typically observed for that hour, weekday and city combination, and dropping days from the dataset in which the majority of hours are viewed as outliers. This process is conducted for all results reported in this article. Through this process, we find that outliers emerge primarily on US holidays (for example, July 4th and Presidents' Day) and on days when weather conditions are sufficiently poor as to restrict travel.

Energy modeling

We evaluate the environmental impact of this experiment by measuring fuel consumption rates and CO_2e emissions of segments impacted by the intervention. Because direct measurements of fuel consumption or CO_2e emissions are impractical, we use scalable methods for estimating fuel consumption rates. CO_2e emissions then naturally arise from these estimates, as carbon emissions are typically modeled as proportional to the fuel consumption in transportation settings[27].

Fuel consumption modeling has been widely studied in the literature[28]. Models of this form roughly fall into two categories: principled models[28], which aim to model the physics underlying energy usage and empirical models[29–31], which fit often nonparametric models to ground-truth fuel consumption data. For this study, we collaborate with the National Renewable Energy Laboratory, integrating models that fall broadly into both categories. These models at their core rely on FASTSim[32,33], a physics-based simulator (hence, a principled model) that calculates the power required to meet a given drive cycle speeds provided other inputs such as road grade and vehicle specifications such as drag, transmission and rolling resistance. Its methodology and data are validated from dynamometer testing data via collaboration with other laboratories (for example, Argonne National Laboratory), so this is a high-fidelity model with many parameters to calibrate toward specific vehicle models. However, FASTSim requires significant computation power and high-frequency GPS location data, which makes it challenging to run for all segments or trips. To address this issue, we use an empirical machine learning model on top of FASTSim, similar to the National Renewable Energy Laboratory's RouteE model[34]. This family of models significantly reduces the computational burden and works well with segment-level speeds, eliminating the need for high-fidelity GPS location data. The ML-based model take as features the properties from segments and estimates the fuel consumption for each segment. Features commonly used by these models include the segment-level speeds, road grade and length. Supplementary Fig. 11 provides a depiction of the employed model for one class of roads. Notably, the convex shape of the model is a commonly known feature by energy modeling practitioners, and denotes that vehicles operating at intermediate driving speeds generally experience the highest levels of fuel efficiency.

Ethical compliance

The study protocol and data use were reviewed by the Stanford University Institutional Review Board (IRB). Based on the analysis involving exclusively non-identifiable data, the IRB determined that this work does not meet the definition of research involving human subjects as defined in 45 CFR 46.102 or 21 CFR 50.3, and therefore did not require formal IRB review.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The data supporting the findings of this study are not publicly available, as they constitute confidential business information. Source data for Fig. 2 are provided with this paper.

Code availability

Source code for the statistical analysis tools used is available via GitHub at https://github.com/google-research/google-research/tree/master/congestion_dispersion.

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Author contributions

Authors are listed alphabetically. N.A. led and assembled the team of multidisciplinary experts, and A.T. oversaw the research project. M.N. and N.A. designed the experiment. T.C., Y.L., K.C. and H.Z. implemented the cost function and segment selection. A.R.K. wrote the data pipelines and analysis code, proving the network effect. E.T. developed the statistical models and analysis. A.B. and S.V. did a thorough validation of the results from a transportation and statistical standpoint. P.R. provided research oversight. A.R.K., S.V., N.A. and A.B. wrote the paper, and all authors gave feedback and contributed to editing the paper. T.C., A.B. and M.N. completed the work while at Google.

Competing interests

All authors are or were affiliated with Google Research, an organization within Google LLC.

Additional information

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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	Aggregated and anonymized metrics from Google Maps Platform
Data analysis	Custom code was developed in python and is available here: https://github.com/google-research/google-research/tree/master/congestion_dispersion; The computational pipeline utilized a suite of Python libraries, including but not limited to NumPy and Pandas for data manipulation, Statsmodels and TensorFlow for statistical modeling, Matplotlib and seaborn for visualization. RouteE (NREL) was used for emissions computation.

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Reporting on race, ethnicity, or other socially relevant groupings	Study utilized aggregated and anonymized metrics from Google Maps. Information regarding race, ethnicity, or other socially relevant groupings was not collected, used, or analyzed
Population characteristics	No specific demographic information was available or used due to the anonymized nature of the dataset.
Recruitment	Study analyzed aggregated trips from existing users of a navigation app. No new participants were recruited for the study.
Ethics oversight	The study protocol and data use were reviewed by the Stanford University Institutional Review Board (IRB) (Protocol Number: 82535). The IRB determined that the project does not meet the definition of human subjects research as defined in federal regulations 45 CFR 46.102 or 21 CFR 50.3, as it involved exclusively non-identifiable data.

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All studies must disclose on these points even when the disclosure is negative.

Study description	This is a large-scale empirical study using a switchback experimental design to evaluate the impact of routing-app interventions on urban traffic congestion and CO2 emissions
Research sample	The sample consists of aggregated, and anonymized metrics from Google Maps trips across 10 major U.S. cities. The sample is representative of navigation-app trips requesting routes within these urban geographies.
Sampling strategy	Road segments (~100 per city) were selected based on high vehicle density at peak demand or the presence of bottlenecks. A marginal routing intervention was applied, affecting under 2% of observed trips to ensure network-wide efficiency without significant impact on individual user travel times.
Data collection	Aggregated and anonymized metrics from Google Maps navigation platform
Timing	Segment-level analysis was conducted over a six-month period, while trip-level analysis used the final two months of the study due to data retention limits. Data were computed at hourly intervals on weekdays between 7:00 AM and 8:00 PM.
Data exclusions	Outliers were removed for time intervals where traffic density fell significantly outside typical values, specifically on U.S. holidays (e.g., July 4th) and days with extreme weather conditions that restricted travel. Supplementary information contains analysis without outlier removal which shows 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.
Non-participation	Not applicable. The study utilized exclusively non-identifiable, aggregated mobility data; the Stanford University IRB determined the project did not meet the definition of research involving human subjects.
Randomization	A switchback experimental design was employed, where the treatment status (routing intervention) for entire geographies was alternated on a daily basis to allow for direct comparison with control intervals.

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Describe the experimental replicates, specifying number, type and replicate agreement.

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Describe the sequencing depth for each experiment, providing the total number of reads, uniquely mapped reads, length of reads and whether they were paired- or single-end.

Antibodies

Describe the antibodies used for the ChIP-seq experiments; as applicable, provide supplier name, catalog number, clone name, and lot number.

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Specify the command line program and parameters used for read mapping and peak calling, including the ChIP, control and index files used.

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Methodology

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Diffusion MRI ☐ Used ☐ Not used

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(See Eklund et al. 2016)

Correction | *Describe the type of correction and how it is obtained for multiple comparisons (e.g. FWE, FDR, permutation or Monte Carlo).*

Models & analysis

n/a	Involved in the study
☒	☐ Functional and/or effective connectivity
☒	☐ Graph analysis
☐	☒ Multivariate modeling or predictive analysis

Multivariate modeling and predictive analysis

The study employs a Hierarchical Bayesian outcome modeling framework to estimate the impact of routing interventions across different cities and hours.