The Short-Run Effects of Congestion Pricing in New York City*

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Abstract

Starting in January 2025, New York City became the first city in the United States to introduce a fee for vehicles entering its central business district (CBD). Using Google Maps Traffic Trends, we show that the policy increased speeds in the CBD, had spillovers onto non-CBD roads, and reduced estimated vehicle emissions throughout the metro area. Relative to a set of control cities, average traffic speeds in NYC's CBD increased by 15% following the introduction of congestion pricing, with larger effects during the most congested hours. Roads commonly traversed on routes to the CBD before the policy have also seen an increase in speeds and a decrease in estimated vehicle CO_2 emission rates. Overall, these speed changes reduced realized travel times on trips to and within the CBD by approximately 8%. The increase in speed is greatest in neighborhoods closer to the CBD, with no significant difference between neighborhoods with different income levels.

JEL codes: **R41, R48, R5**

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1 Introduction

In January 2025, New York City became the first city in the US to implement cordon-based congestion pricing. Under the new policy, passenger vehicles entering the central business district (CBD) during peak hours (5am-9pm on weekdays and 9am-9pm on weekends) are assessed a $9 toll, with higher prices for vans and trucks and lower prices for taxis and during the remaining off-peak hours. The policy comes after decades of debate and multiple false starts. Proponents of congestion pricing point to its potential to reduce traffic, lower emissions, and generate critical funding for public transportation improvements. From the perspective of classical economics, congestion pricing is also a natural way to address the externalities that drivers impose on others (Pigou, 1932; Vickrey, 1952). However, opponents argue that congestion pricing will not change traffic flows in the long run and may induce harmful economic impacts, including unfair burdens on lower-income individuals.

In this paper, we study the short-run effects of the New York City (NYC) congestion pricing policy on road speeds, travel times, and emissions throughout the NYC metropolitan area. To estimate the impact of the policy on each outcome, we apply a consistent generalized synthetic control design (Xu, 2017) that compares observed outcomes in NYC after the policy was introduced against a synthetic control formed from concurrent outcomes observed in other major US cities. We primarily use aggregated and anonymized statistics from Google Maps Traffic Trends, which we complement with information on air quality from PurpleAir and neighborhood demographics from the Census Bureau.

The introduction of congestion pricing led to an immediate increase in speeds within NYC's CBD, which has persisted since implementation. Average speeds on CBD road segments increased from 8.2 miles per hour (mph) during weekday peak hours in the months before implementation to 9.7 mph in the two months following implementation. However, comparing these raw changes in speeds conflates the impact of the policy with any time trends in traffic patterns. Even though only NYC implemented congestion pricing, average speeds in most cities were higher in January and February than in the preceding months. Relative to a synthetic control formed from other cities, we estimate that speeds in NYC's CBD increased by 15%, suggesting that most of the observed change in speeds is attributable to the impact of congestion pricing. The effects on speeds are even larger during the afternoon—historically the most congested time of day—and persist even after peak-hours pricing ends at 9pm.

While only entries into the CBD are priced, road networks are interconnected and pricing any subset of roads may have spillover effects throughout the network. Ex-ante, the direction of possible spillovers on non-CBD road segments is ambiguous. The policy may have positive spillovers on non-CBD speeds if it reduces the total number of trips throughout the city, or negative spillovers if non-CBD roads are used as substitutes for driving to/from the CBD. In a survey of economists before the policy's implementation, 90% of respondents agreed that congestion pricing in NYC would "lead to a substantial reduction in traffic congestion in the targeted area," but the majority were uncertain as to whether traffic would increase on roads just outside the CBD (Clark Center Forum, 2024). To quantify these spillovers, we measure segment-level exposure to the policy based on pre-policy *co-occurrence* with trips into the CBD. A road segment has a co-occurrence of 50% if half of the cars that typically traversed it prior to the policy eventually entered the CBD. If the policy's main effect were to reduce CBD trips by 10% uniformly, a segment with 50% co-occurrence would see a proportional 5% decrease in cars. Road speeds are non-linear in traffic volumes and substitution effects may compensate for the decrease in CBD trips, so the effects on speeds across co-occurrence levels remain ex-ante ambiguous.

We find that the policy had positive spillovers on speeds throughout the NYC metropolitan area, with larger effects on roads with high levels of co-occurrence with the CBD. For roads outside the CBD with 80-100% co-occurrence—which include the Lincoln Tunnel, Holland Tunnel, and other main entries to the CBD—we estimate that the policy's implementation increased speeds by 16%. The effects then decline monotonically in the level of co-occurrence. Speeds on roads with just 0-20% co-occurrence experienced a smaller 4% increase in speeds. Across road types, highways experienced larger increases in speeds—especially at lower levels of co-occurrence—while the effects on local and arterial roads have been more limited.

The changes in road speeds add up to meaningful differences in travel times between different parts of the city. For trips to the CBD, the implementation of congestion pricing increased average speeds by about 8%. The average trip to the CBD in the months preceding the policy's implementation took 36 minutes. For a hypothetical driver traveling to the CBD every weekday, the 8% increase in speeds on trips to the CBD adds up to 12.5 hours of saved time each year. While drivers on trips to the CBD must now pay a toll for these time savings, drivers on other trips benefit from increased speeds without changes in price. Speeds on trips within the CBD also increased by 8%, while speeds on trips leaving the CBD increased by a more minor 3%. For trips entirely outside of the CBD, average speeds increased by just 1%.

Beyond traffic externalities on other drivers, congestion also imposes environmental externalities. We infer emission rates using an engineering model that transforms speed profiles and segment characteristics into an estimate of CO_2 emissions per 100 kilometers traveled, similar to the approach in Brooker et al. (2015).[1] Overall, the change in traffic patterns following the introduction of congestion pricing reduced the CO_2 emission rates by 2-3% for cars traveling in the CBD and on roads with high co-occurrence. However, we find no detectable effect on ambient concentrations of fine particulates ($PM_{2.5}$), an important local air pollutant. Applying the same synthetic controls methodology to $PM_{2.5}$ air quality measures from PurpleAir sensors, we find no effect on $PM_{2.5}$ in the weeks following the policy's implementation, although the estimates are imprecise.

To help explain the impacts on road speeds, we model the non-linear relationship between speeds and the density of cars on affected road segments (the "congestion function"). As is well documented in the traffic engineering literature, congestion functions are often convex, especially on highways (Seo et al., 2017). As a result, the effects on speeds of a constant change in density depend on *where* along the congestion function pre-policy traffic typically operated. If a road is near free-flow or far past a bottleneck threshold, removing even 10% of traffic density would likely leave speeds unchanged. However, if the road is operating near a steep part of its congestion function, removing even a few cars can substantially increase speed. Focusing on the key entry points into the CBD, we show that, while

[1] We do not observe the vehicle type. CO_2 emission rates are estimated assuming all vehicles are a standard mid-sized sedan.

the Queensboro Bridge and Holland Tunnel have experienced similar changes in density following the policy's implementation, the change in speeds has been over 5mph larger on the Queensboro Bridge as it was operating at a steeper part of its congestion function. The estimated congestion functions also provide a tool for evaluating the potential gains of further reductions in traffic densities, such as those stemming from future increases in the toll to enter the CBD.

Finally, we explore whether the effects of congestion pricing vary across neighborhoods of different income levels, distances from the CBD, and in specific areas of interest such as New Jersey and the Bronx. Critics of congestion pricing commonly raise concerns over the potential adverse effects on lower-income residents (Ecola and Light, 2009; Taylor, 2010). We group Census tracts by the quintile of median household income and estimate the effects for each group of tracts separately. We find that the policy has increased speeds on segments within each quintile by a similar amount. Similarly, trips to the CBD originating in each income quintile have all seen speed gains of 8-9%. Distance from the CBD is a more important predictor of heterogeneity in the policy's effects. The effects on segment-level speeds and speeds on trips to the CBD are largest in tracts closest to the CBD and decrease monotonically as we move to tracts farther out. For New Jersey residents, the policy increased speeds on road segments within Hudson and Bergen counties by 3%, and reduced travel times to the CBD by 8%. For Bronx residents, congestion pricing has also reduced travel times to the CBD, although average speeds on segments within the Bronx itself declined by 2.5%.

Our work most directly contributes to a set of early evaluations of the New York City congestion pricing program. Even before the policy's implementation, work by the MTA (2022) and Hierons (2024) attempted to anticipate the policy's potential impacts on congestion, air pollution, and mode choice. Since its launch, year-to-year comparisons in speeds and travel times in NYC's CBD have been reported by journalists (Gordon et al., 2025; Ley, Hu and Collins, 2025), the Congestion Pricing Tracker website (Moshes and Moshes, 2025), and the Metropolitan Transportation Authority (MTA, 2025), and others. Perhaps due to having access to limited data covering only subsets of NYC roads, however, these early analyses occasionally disagree on basic questions such as whether the program decreased or increased travel times (Hu, Ley and Schweber, 2025). In contrast to these existing studies, we evaluate the causal effects of congestion pricing using a consistent econometric strategy and large-scale data covering both NYC and a set of comparison cities.

A larger body of work studies existing congestion pricing policies in London, Stockholm, Milan, and elsewhere.[2] Following its implementation of cordon-based congestion pricing in 2003, downtown London saw reduced traffic, lower pollution, and fewer accidents (Leape, 2006; Green, Heywood and Paniagua, 2020; Tang and van Ommeren, 2022). Similar effects on downtown traffic conditions have been documented for congestion pricing in Stockholm (Eliasson et al., 2009; Simeonova et al., 2021) and Milan (Gibson and Carnovale, 2015). Evidence of spillovers onto other roads is more mixed. Herzog (2024) finds that London's policy reduced traffic on non-priced roads that lead into the downtown area, while Gibson and Carnovale (2015) finds that traffic increased on radial roads offering a substitute to traveling to downtown Milan. Public sentiment has also been found to evolve quickly around launch.

[2] A related set of studies conduct ex-ante simulations of *potential* congestion pricing policies in cities without any existing policy, including in Chicago (Almagro et al., 2024), Beijing (Barwick et al., 2024), Paris (Durrmeyer and Martínez, 2024), Bangalore (Kreindler, 2024), and Tel Aviv (Ater et al., 2025).

In Stockholm, only 36% of residents were in favor of the policy before the policy's launch—similar to the 29% support among New York residents in December 2024 (Greenberg, 2024)—but public support increased to 66% just a year later.

In the absence of congestion pricing, other work studies the effects of alternative congestion mitigation strategies. Duranton and Turner (2011) and Hymel (2019) show that the increases in road capacity have little effect on speeds thanks to a proportional increase in vehicle miles traveled, supporting an early hypothesis by Downs (1962) that the "induced demand" from marginal drivers will offset any gains in speeds. Driving restrictions and car-free zones in cities such as Santiago, Mexico City, and Paris can reduce downtown congestion and pollution, but are inefficiently targeted and do not raise any revenue (Davis, 2008; Gallego, Montero and Salas, 2013; Yang, Purevjav and Li, 2020; Sleiman, 2021; Galdon-Sanchez et al., 2022). Other cities—including many in the US—have introduced dedicated highway toll lanes that run adjacent to existing lanes and are dynamically priced in response to existing traffic conditions. While such lanes offer drivers the option to pay for faster speeds when needed, they may increase congestion in the remaining free lanes (Hall, 2018; Bento, Roth and Waxman, 2020; Cook and Li, 2024).

2 Empirical Setting & Data

2.1 Congestion Pricing in NYC

New York City's congestion pricing policy, officially known as the Central Business District Tolling Program, was implemented on January 5th, 2025. The initiative imposes a fee on vehicles entering Manhattan south of 60th Street, excluding the FDR Drive and West Side Highway. The tolls are collected electronically and vary based on the time of day, vehicle type, and whether the vehicle is equipped with an E-ZPass transponder. Since the policy's launch, nearly 270,000 passenger cars have entered the CBD on the average weekday.[3] The Metropolitan Transportation Authority (MTA) anticipates that the tolls will generate approximately $15 billion, which will be allocated to fund repairs and enhancements to the city's subway, bus, and commuter rail systems.

Toll rates are set at $9 per day for passenger cars and small commercial vehicles if paid by E-ZPass. Motorcycles pay $4.50 per day, while trucks and buses pay between $14.40 and $21.60 per day depending on their size. These rates are reduced by 75% overnight and are up to 50% higher if drivers do not have E-ZPass and are instead sent a bill by mail. Taxis and ridesharing vehicles pay a per trip (rather than per day) rate of $0.75 for taxis and $1.50 for ridesharing vehicles for trips that start, end, or pass through the CBD.[4] There are a few exempted vehicles (e.g., emergency vehicles), and vehicles entering via certain bridges or tunnels that are already tolled receive a partial credit. Low-income residents can also receive 50% off after their first ten trips in a month. The rates are scheduled to

[3] This statistic is computed based on the publicly-available "MTA Congestion Relief Zone Vehicle Entries" dataset (source) for weekday entries by "Cars, Pickups and Vans" between January 5th and February 28th, 2025. This does not include taxis or ridesharing vehicles.

[4] Ostrovsky and Yang (2024) evaluate the pricing by vehicle type and argue that the small per-trip charge on taxis and ridesharing companies is too low, as a single trip by a taxi likely contributes as much congestion as a trip by a private vehicle.

increase over time. The passenger car rate is set to increase to \$12 in 2028 and \$15 in 2031.

The concept of congestion pricing in New York City has a history spanning several decades. In the early 1970s, Mayor John Lindsay proposed tolling East River crossings to mitigate traffic congestion in Lower Manhattan, but the plan was eventually withdrawn after facing stiff opposition from the trucking industry, taxi drivers, and local businesses concerned about the financial impact of tolls. Subsequent mayors also attempted to implement similar measures. In 2007, Michael Bloomberg's administration proposed the PlaNYC initiative, which aimed to introduce congestion pricing to promote sustainability and fund transportation infrastructure. While this proposal stalled in the state assembly, it resurfaced in 2017 when Governor Andrew Cuomo advocated for congestion pricing to raise funds for improving transit. This led to its eventual inclusion in the 2019 state budget and, after many delays, its implementation in 2025.

The policy encountered criticism and legal challenges while under development. Critics argue that this approach imposes an additional financial burden on residents, may have adverse economic impacts on business, and will shift traffic and pollution to other parts of the city (Ley, 2022). Some businesses have responded by adding surcharges to deliveries and services within the toll zone, effectively passing the cost onto consumers. At least ten lawsuits were filed against the MTA and state officials by business coalitions, elected officials from New Jersey, and others (Hu and Ley, 2024).

2.2 Data

We use two sets of aggregated and anonymized outcome statistics from Google Maps Traffic Trends: 1) segment-level outcomes, which we then aggregate in time and space across sets of road segments; and 2) origin-destination (OD) level outcomes, aggregated across trips based on OD Census tract characteristics. Our primary sample covers traffic conditions from September 2024 through February 2025. We use Philadelphia, Boston, Chicago, Atlanta, and Baltimore to form synthetic controls for all traffic-related outcomes. Except where otherwise noted, all analyses focus on data from weekday peak hours (5am-9pm).

Segment-level outcomes. We focus our analysis of segment-level outcomes on groups of segments aggregated by geographic location, such as within specific Census tracts, or by shared characteristics, such as co-occurrence with the CBD. Road segments vary in length, with an average of approximately 50 meters. For each segment-level outcome, we consider aggregates composed of the harmonic mean weighted by traversal distance. That is, for a given outcome y measured across segment group j in hour t, we consider the hourly distance-weighted average outcome:

$$\bar{y}_{j,t} = \frac{\sum\limits_{s \in S_j} d_{s,t}}{\sum\limits_{s \in S_j} d_{s,t}/y_{s,t}} \tag{1}$$

where S_j is the set of traversals through segments s in segment group j, and $d_{s,t}$ is the traversal distance (equivalent to the length of each segment). We consider three types of outcomes: traversal speed, normalized traversal speed relative to the segment's speed limit, and the estimated emission rate $e_s(t)$.

Origin-destination level outcomes. We augment our segment-level analysis with several OD-level outcomes. For each OD, we consider average realized travel times and average realized trip speeds (e.g. travel time divided by trip length). We categorize ODs based on origin Census tract characteristics and whether the OD starts and/or ends within the CBD. We use the average statistic within each set of ODs in each hour, weighting each trip equally.

Air quality. We use air quality data from PurpleAir to estimate the effects of the policy on pollutant levels in New York City. PurpleAir is a company that sells $PM_{2.5}$ sensors as a consumer product. Its customers can opt to share the data their sensors gather with the public, and the many "community scientists" form a network of $PM_{2.5}$ monitoring with large coverage. We focus on the effects on $PM_{2.5}$ over other pollutants as this pollutant accounts for most of the adverse health effects of air pollution in the U.S. (Tschofen, Azevedo and Muller, 2019; National Institute of Environmental Health Sciences, 2024), and we use the specific $PM_{2.5}$ measurement recommended by PurpleAir Community (2023).

For each city, we query the data of all outdoor PurpleAir sensors in the corresponding Core-Based Statistical Areas (CBSA). In New York City, we use 323 unique outdoor PurpleAir sensors that were actively collecting data for at least the period of January 5th, 2025, to February 8th, 2025, of which 24 are in the CBD. Few potential control cities have sufficient sensors, and some have zero total sensors within the CBD. Ultimately, we use data from Chicago, Cincinnati, Charlotte, Dallas, Minneapolis, Philadelphia, Phoenix, Portland, and Washington, D.C.

City and CBD boundaries. We define city boundaries according to the corresponding CBSA for NYC and a collection of control cities.[5] For NYC, we define the CBD as the congestion pricing zone. For control cities, we define the CBD using the most prominent version of a CBD drawn by a city government-affiliated organization in each control city. We use such definitions because the congestion pricing cordon area aligns with the NYC CBD defined by the City of New York before it released any plans for a lower-Manhattan congestion pricing policy (NYC Department of City Planning, 2011). If no city-affiliated organization has defined a CBD, we check for a definition of the city's downtown area instead among the same and similar organizations. References to the official sources we use to define the CBD shapes in control cities can be found in Appendix A.1.

3 Empirical Strategy

Generalized Synthetic Controls (GSC). Assessing the effects of New York City's congestion pricing policy is complicated by numerous confounding factors. A straightforward comparison of average outcomes before and after the policy combines the policy's effects with any other time-varying factors influencing traffic conditions. Existing evidence generally compares average traffic patterns in NYC after implementation to earlier months or to data from the prior year. Interpreting the results

[5]The full name for NYC's CBSA is the New York-Newark-Jersey City CBSA.

from such approaches as causal requires an assumption that, absent the policy, NYC traffic conditions after January 5th would have been similar to earlier periods. We introduce a method that instead compares changes in traffic conditions in NYC to contemporaneous changes in a set of comparison cities.

Specifically, we adopt the generalized synthetic control (GSC) methodology introduced by Xu (2017). The strategy relies on comparing changes in NYC before and after the policy to changes in outcomes observed in other cities, which are combined into a "synthetic control" for NYC using pre-policy data to estimate weights. The GSC method extends the classical synthetic control approach (Abadie, Diamond and Hainmueller, 2010) by incorporating interactive fixed effects, such that unobserved confounders may vary both across units (e.g., cities) and over time. This approach identifies the causal effect of the policy under the weaker assumption that, absent the policy, NYC's outcomes would have tracked the estimated 'counterfactual' outcomes, which are constructed from data in control cities weighted to match pre-policy patterns.

More formally, let $Y_{it}(0)$ denote the potential outcome for unit i at time t if untreated and $Y_{it}(1)$ denote the potential outcome if treated. We only observe

$$Y_{it} = D_{it}Y_{it}(1) + (1 - D_{it})Y_{it}(0)$$

where D_{it} is an indicator that takes the value 1 if city i is treated at time t, and 0 otherwise. In our application, $D_{it} = 1$ for NYC after implementing the congestion pricing policy, and $D_{it} = 0$ otherwise. The set of potential control cities (Boston, Philadelphia, Chicago, etc.) remains untreated throughout the sample period, allowing them to serve as comparisons.

Following the GSC framework, we assume that the untreated potential outcome $Y_{it}(0)$ can be decomposed into a low-rank factor structure plus some idiosyncratic noise:

$$Y_{it}(0) = \alpha_i + \gamma_t + \boldsymbol{\lambda}_i^\top \mathbf{f}_t + \varepsilon_{it} \tag{2}$$

where α_i is a unit (city) fixed effect, γ_t is a time fixed effect, $\boldsymbol{\lambda}_i$ is a vector of factor loadings specific to unit i, $\mathbf{f}_t$ is a vector of common factors, and ε_{it} is an idiosyncratic error term. The functional form can be extended to include time-varying unit characteristics, although we do not use such characteristics in our setting.

Estimation. We first estimate these factors and loadings from the panel data of outcomes observed in the pre-treatment period. The estimated factors and loadings are estimated separately for each outcome variable. Intuitively, this step aims to identify the factors and loadings that best capture the changes in the outcomes in each unit across time. Using the estimated parameters, we can then predict *counterfactual* outcomes $\hat{Y}_{it}(0) = \hat{\alpha}_i + \hat{\gamma}_t + \hat{\boldsymbol{\lambda}}_i^\top \hat{\mathbf{f}}_t$ for each post-treatment period $t > T_0$ (where T_0 is the time period that congestion pricing began).

The Average Treatment on the Treated (ATT) effect in period $t > T_0$ is given by:

$$\widehat{\text{ATT}}_t = \frac{1}{|\mathcal{I}_r|} \sum_{i \in \mathcal{I}_r} Y_{it} - \hat{Y}_{it}(0) \tag{3}$$

where $\mathcal{I}_r$ is the set of treated units. We will often report the aggregate ATT, too, which is estimated as $\widehat{ATT} = \frac{1}{T-T_0}\sum_{t>T_0}\widehat{\text{ATT}}_t$. We implement this procedure using the *gsynth* package for R provided by Xu (2017). We use cross-validation to select the dimensionality of the factors and, for inference, we use parametric standard errors.

Identification. The key assumption of the GSC approach is that the error term ε_{it} is independent of treatment assignment, time and unit fixed effects, and the unobserved cross-unit ($\boldsymbol{\lambda}_i$) and cross-time ($\mathbf{f}_t$) sources of heterogeneity. This assumption has three important implications. First, the factor loadings $\boldsymbol{\lambda}_i$ must be stable over time. If a structural break changes the fundamental relationship between cities, this stability may be violated, leading to poor counterfactual predictions during the treated period. Second, much like traditional differences-in-differences (DiD), the GSC requires that the exact timing of treatment is exogenous after conditioning on the factor structure. Finally, this assumption is violated if there are spillover effects from NYC to control cities (e.g., large-scale traffic diversions or copy-cat policy changes).

This assumption is generally weaker than the standard DiD assumption that, in the absence of treatment, treated and control groups would follow parallel trends. Instead, GSC allows for multiple time-varying confounders that affect units differently. This is particularly valuable in contexts like urban traffic, where many latent factors (e.g., economic cycles, seasonal weather patterns) may affect different cities in different ways.

4 Impacts on Road Conditions and Emission Rates

In this section, we examine the effects of congestion pricing on road conditions, travel times, and emissions throughout the NYC metro area. We find that the policy increased speeds and reduced the emission rates on road segments within the CBD, and, through a spillover effect, on segments outside the CBD that had a high level of "co-occurrence" with trips to the CBD. The increased speeds add up to lower observed travel times across the city.

4.1 Speeds within the CBD

The average speed on road segments in the NYC CBD increased from 8.2 mph in the four months preceding the policy's implementation to 9.7 mph in the 2 months after implementation (Figure 1 Panel a). The increase in raw average speeds is consistent across highways, arterial, and local roads (Figure B.1). However, this increase in speeds before and after the policy's implementation is not unique to NYC. In fact, average speeds in the CBDs of *all* cities in our primary sample were higher after January 5th than in the preceding months (Table B.1).

To what extent is the observed increase in speeds in NYC's CBD attributable to the effects of the policy? To evaluate this, we compare speeds in the NYC CBD to speeds in the CBDs of other cities by estimating Equation (3) using average speeds in each CBD over time. Figure 1 Panel b) plots the day-level ATT on log speeds for CBD road segments during weekday priced hours. Prior to the policy's launch, speeds in NYC were similar to the counterfactual speeds constructed from the set of comparison cities, suggesting that the GSC approach is able to capture trends across cities accurately. After the onset of congestion pricing, average speeds in the CBD increased sharply by 15% relative to the synthetic control and have remained elevated since. Under the assumptions of the GSC approach, this suggests that the policy's causal impact accounts for over three-fourths of the change in average speeds.

The effects of congestion pricing on CBD speeds are concentrated in the afternoon and early evening hours on both weekdays and weekends. Before the policy's implementation, average speeds in the CBD ranged from 15 mph in the morning to half that in the late afternoon (Figure 1 Panel c). Speeds on the weekends remain elevated later into the morning than on weekdays, before hitting a nadir of about 8 mph in the early evening. To evaluate how the policy's effect on speeds varies by time of day, we separately estimate Equation (3) for each two-hour time window between 3am and 11pm. In the early morning, the policy had only a small and statistically insignificant effect on average speeds. Starting around 11am, the positive effect on speeds becomes more substantial, increasing to about 15% on both weekdays and weekends. On weekdays, the effect sizes peak between 1-7pm when the policy has increased speeds by over 20%. On weekends, the largest effects are between 3pm-9pm and reach over 25%. Speeds remain elevated even after peak hour pricing ends each day.

4.2 Spillovers on non-CBD Roads

Cities are interconnected and policies that affect one area invariably affect the entire city. While only trips into the CBD are priced, many of these trips traverse substantial lengths of road outside the CBD. If the policy reduces the number of such trips or causes substitution to unpriced routes, the speeds on non-CBD segments may also change after its implementation.

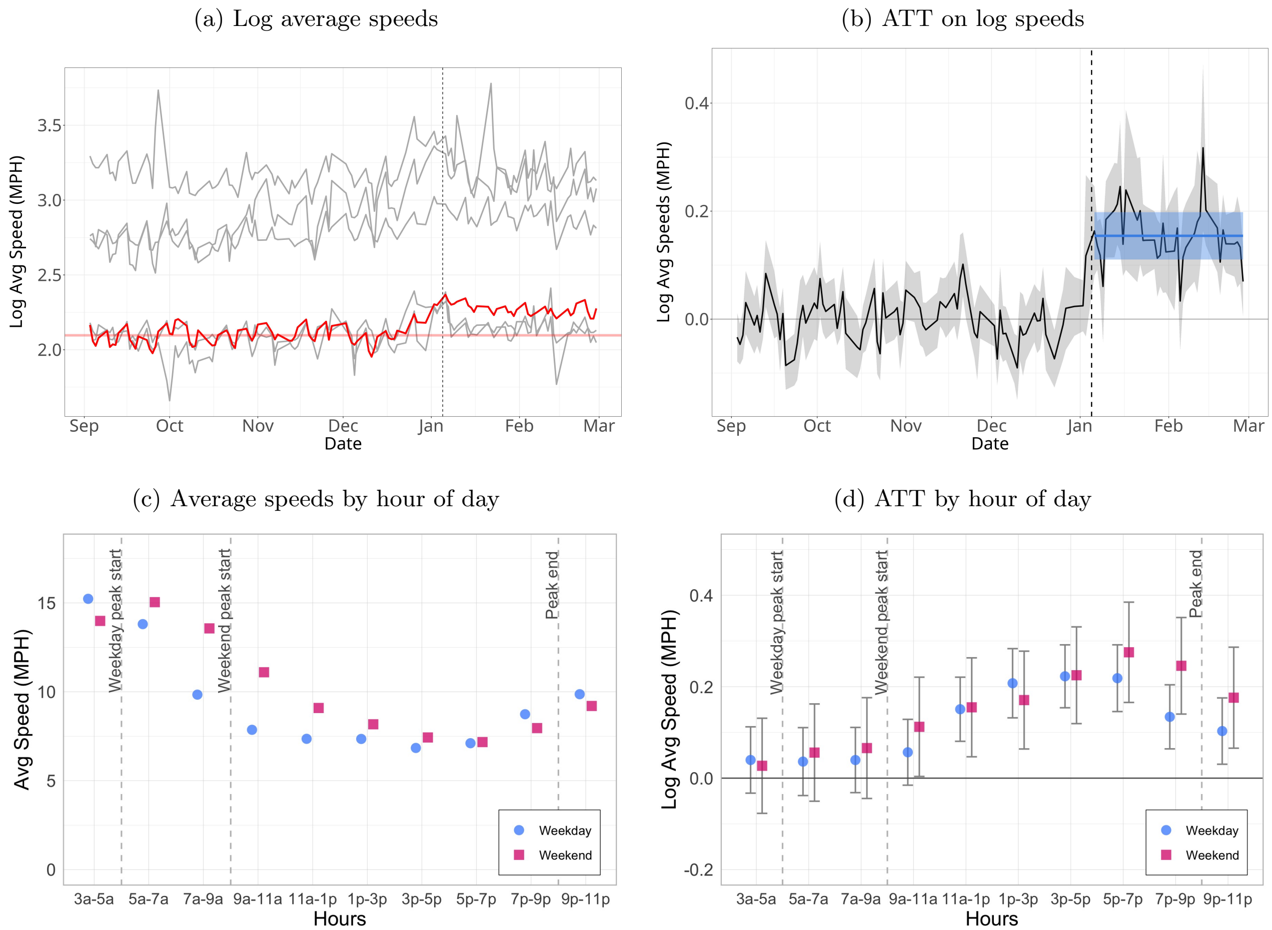
We define a segment-level measure of exposure to the policy based on each segment's "co-occurrence" with trips to the CBD. Intuitively, segments that are frequently traversed as part of trips to the CBD are more exposed to the policy than segments that are rarely part of such trips. Let S_{CBD} be the set of segments within a CBD, and let R be the set of observed trips within a given timespan, where each trip $R_i = \{s_1, \dots, s_N\}$ denotes the set of segments $s_j,\ j = 1, \dots, N$ traversed from origin to destination. For each segment s, we define its co-occurrence with the CBD C_s as

$$C_s = \frac{|\{R_i \in R \mid s \in R_i \wedge S_{\text{CBD}} \cap R_i \neq \phi\}|}{|\{R_i \in R \mid s \in R_i\}|}, \tag{4}$$

or stated plainly, as the fraction of trips passing through segment s which also pass through at least one of the segments $s_i \in S_{\text{CBD}}$. We compute each segment's co-occurrence with the CBD using data from September to November 2024 and hold them fixed for the rest of the analysis. Figure A.1 maps road segments by their level of co-occurrence.

The policy increased speeds on roads throughout the NYC metro area, with the largest effects on those roads that are most exposed to the policy (Figure 2). To show this, we estimate the treatment effect of congestion pricing separately for different bins of co-occurrence levels using segments in other cities that have similar levels of co-occurrence with their respective CBDs to form a synthetic control. Non-CBD road segments with 80-100% co-occurrence—that is, road segments for which 80-100% of

Figure 1: Effects on speeds in the CBD



Notes: Panel a) documents the log volume-weighted average daily speed in the CBD of NYC (in red) and a handful of comparison cities (in grey). The horizontal red line indicates the average of NYC speeds between September 1 and December 15, 2024. Panel b) documents the day-level ATT of congestion pricing over time on weekday CBD speeds during peak hours, using data on average speeds by two-hour bin in each CBD. The horizontal blue line is the aggregate ATT for all post-treatment periods. Panel c) reports the average pre-policy speeds in the NYC CBD by hour of the day. Panel d) estimates the treatment effect for each hour bin separately, using data from all other cities and hour bins as potential controls. Shading in Panel b) and vertical bars in Panel d) denote 95% confidence intervals. Standard errors are clustered at the city-level.

traversals pertained to trips entering the CBD prior to the policy—experienced a 16% increase in speeds. The estimated effect for the 80-100% bin is larger—although not statistically different—than the estimated effect on speeds within the CBD. This is consistent with early evidence from the Congestion Pricing Tracker, which showed larger changes in speeds on bridges leading into the CBD than within the CBD itself (Moshes and Moshes, 2025). The effects then decrease monotonically in pre-policy co-occurrence, but even road segments with 0-20% pre-policy co-occurrence have experienced a 4% increase in speeds.

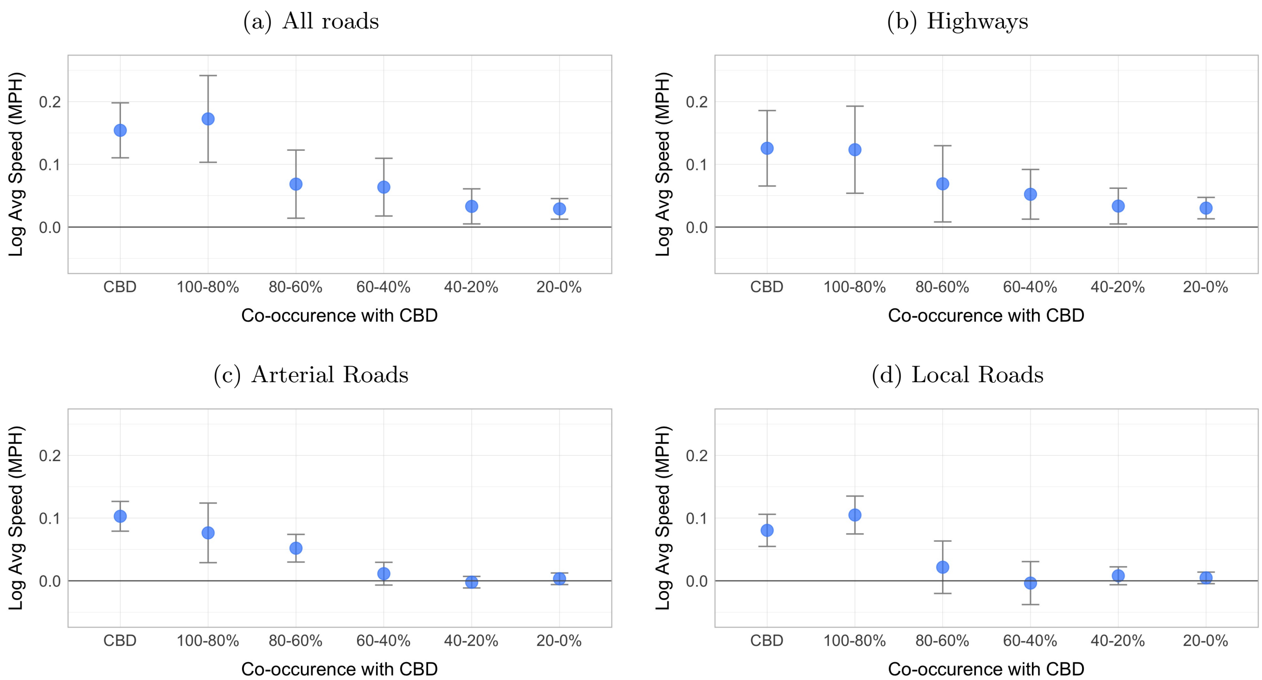
The effects also vary by road type. Highways saw the greatest gains in speed, while arterial and local roads saw smaller gains. Within the CBD, the policy increased highway speeds by 13%, arterial speeds by 10%, and local road speeds by 8%.[6] The larger 16% total increase in speeds within the CBD

[6]There are few highway segments within the CBD, as the FDR Drive and West Side Highway connections to West

suggests that the policy also changed the composition of roads taken within the CBD, from slower local roads to faster arterial and highway roads. Outside of the CBD, congestion pricing increased speeds on highways throughout the metro area. Even highways with only 0-20% co-occurrence with the CBD experienced a 2.5% increase in speeds. However, for arterial and local roads outside of the CBD, the policy had no effect on speeds for segments with lower levels of co-occurrence—even those with 40-60% co-occurrence.

Our finding that no co-occurrence bin decreased in speed was not ex-ante guaranteed. Drivers seeking to avoid the congestion fee may have substituted from roads commonly used to go into the CBD to other roads with different levels of co-occurrence. While we find no evidence that the policy has decreased average speeds for any road type or co-occurrence bin, the potential for traffic diversion has led to concerns among policymakers that certain areas may face increased traffic and emissions from drivers. We further explore the effects on specific areas of concern in Section 6.

Figure 2: Treatment effect on log speeds by CBD co-occurrence and road-type



Notes: This figure documents treatment effects split by levels of co-occurrence and type of road segment. Each point is separately estimated using the average speeds in two-hour bins for segments with the corresponding level of co-occurrence and road segment type for both NYC and the comparison cities. Vertical bars represent 95% confidence intervals. Standard errors are clustered at the city-level.

4.3 Effects on Car Trips

The increases in speed within and around the CBD add up to meaningful differences in travel times for NYC drivers. We define four types of trips based on whether they start or end from inside or outside of the CBD. Only trips that start outside the CBD and end inside it ("to CBD") are subject to pricing

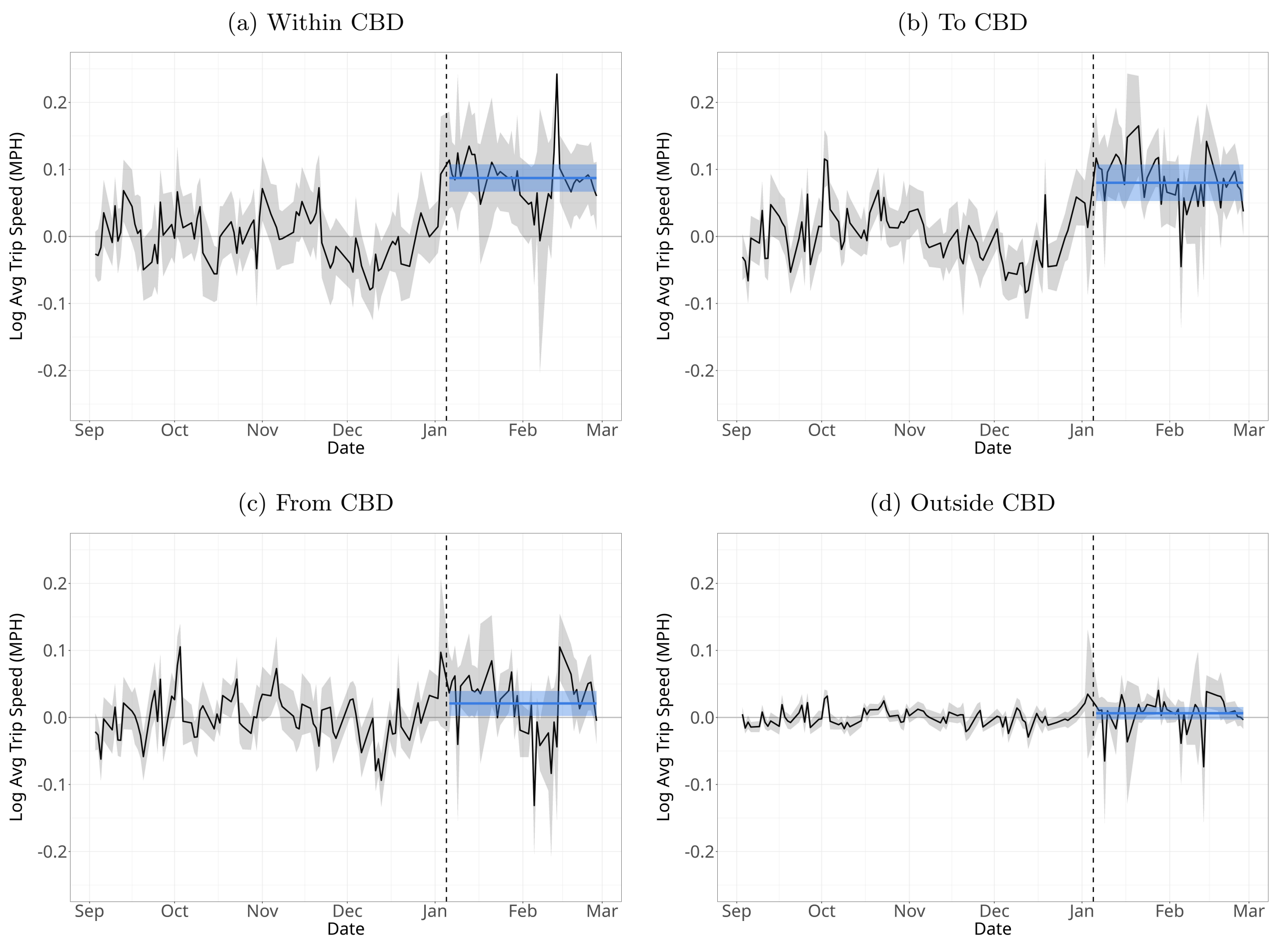
Street are exempted from congestion pricing unless drivers exit into the CBD. The CBD highway segments include just the exit/entry segments connecting highways to the CBD.

(excluding taxi/ridesharing trips), but trips traversing roads that are within or highly exposed to the CBD may also be affected given the evidence above on the policy's spillovers.

Figure 3 plots the day-level ATT on log average trip speeds within each origin-destination category. The implementation of congestion pricing increased speeds on the average trip within or to the CBD by 8%. Speeds on trips traveling from the CBD to areas outside the CBD have also increased, albeit by a smaller 2.5%. The average trip that both starts and ends outside of the CBD has experienced an even smaller increase of about 1% in average speeds, although the effect is not statistically distinguishable from zero.

We focus on average trip speeds (i.e., distance over duration) instead of trip durations to account for compositional differences in the types of trips being taken that could lead to longer or shorter trips. If the policy disproportionately deters shorter trips to the CBD, this may appear as an *increase* in average trip duration despite the speed increases. Figure B.3 plots the ATTs on log average trip duration instead of speeds. In general, the effects on trip durations are smaller than the effects on speed, suggesting that the marginal trip deterred by the policy is shorter than the average trip.

Figure 3: Treatment effect on trip speeds



Notes: This figure documents the day-level ATT on average realized trip speeds, split by whether the trip starts and/or ends in the CBD. The underlying data are the aggregate speed for each city, OD type, and two-hour bin. The horizontal blue lines are the aggregate ATTs for all post-treatment periods. Shaded areas represent 95% confidence intervals. Standard errors are clustered at the city-level.

4.4 CO_2 Emission Rates and Ambient Air Pollution

Changes in traffic patterns also affect the quantity and location of vehicle emissions. CO_2 emissions impose externalities worldwide. Emissions of local air pollutants such as NOx, CO, and particulates impose an externality on nearby residents, which decays exponentially with distance from the road. Although it varies with factors such as terrain and weather, the decay rate for local air pollutants is steep and air quality generally reaches 'background levels' beyond a few hundred meters (Brugge, Durant and Rioux, 2007; Liu, Chen and Xue, 2019). Exposure to vehicle emissions has been found to have negative effects on infant (Currie and Walker, 2011; Knittel, Miller and Sanders, 2016) and adult (Buckeridge et al., 2002) health outcomes.

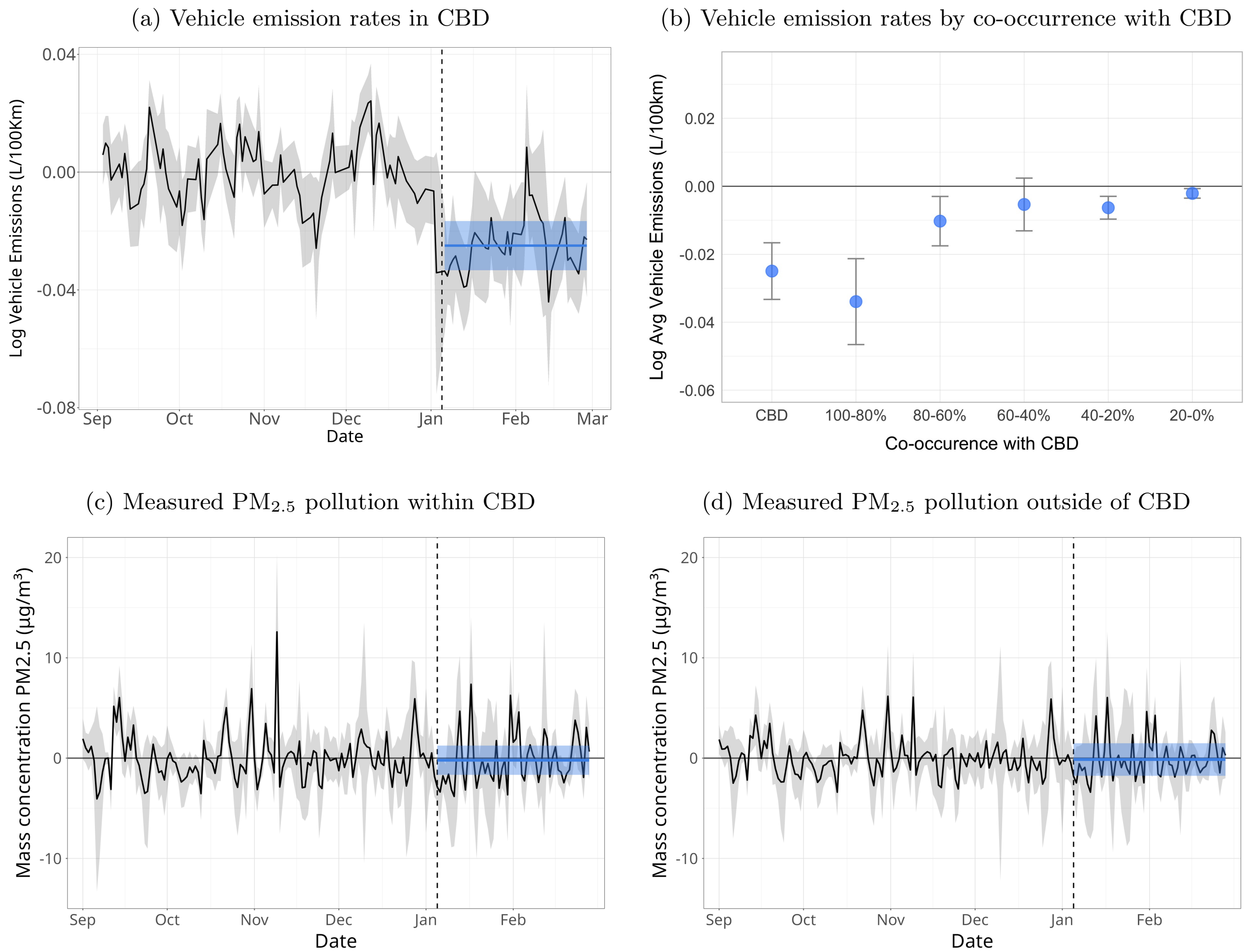
We first measure the effect on CO_2 emission rates per kilometer driven, which can also be thought of as vehicle fuel efficiency. While we cannot directly observe emission rates, we collaborate with the *National Renewable Energy Laboratory* (NREL) to model how they vary based on vehicle speeds and the characteristics of segments they traverse. Appendix A.3 provides additional details.

We find that the change in traffic patterns translates into a modest decrease in the estimated emission rate of vehicles traversing CBD segments. Following the onset of congestion pricing, the estimated emission rates for vehicles traveling within the CBD decreased by 2.5% (Figure 4). Vehicles traveling on segments with high co-occurrence to the CBD have similarly reduced their emission rates, while the effects for vehicles traveling on segments with less than 80% co-occurrence are minimal.

Of course, CO_2 emission rates per kilometer driven are different than overall CO_2 emissions, as the latter depends also on kilometers driven. The primary drivers of CO_2 emission rates are vehicle speed profiles and the segment type. At slow speeds, small speed increases can substantially improve fuel consumption and, correspondingly, reduce the emissions per distance traveled (Figure A.2). Changes in speed or the relative volumes on local roads compared to highways will result in different estimated levels of emissions. While our data cannot directly speak to treatment effects on kilometers driven, data from the MTA on entries into the CBD suggest that the number of trips within the CBD has dropped (MTA, 2025), such that *total* CO_2 emissions may have fallen by even more than our estimates on the effects on the emission *rates* suggest.

We next measure the effects of congestion pricing on ambient concentrations of fine particulates, an important local air pollutant. We use a similar empirical strategy as for other outcomes and compare the daily average $PM_{2.5}$ for PurpleAir sensors inside and outside of the NYC CBD to synthetic controls formed from other cities. As shown in Figure 4, the estimated treatment effect after the policy's implementation is statistically indistinguishable from zero, and the magnitudes of the point estimates are negligible. We caution that the estimates are based on only a handful of PurpleAir sensors and, given how quickly emissions decay with distance, may not capture effects on all parts of the CBD. Evidence from other cities—including London (Green, Heywood and Paniagua, 2020) and Stockholm (Simeonova et al., 2021)—find that similar congestion pricing polices reduced long-run pollution.

Figure 4: Treatment effects on vehicle emission rates and local air pollutants



Notes: Panel a) documents the day-level ATT of congestion pricing on log emission rate, as estimated by Google's internal model, with units corresponding to estimated CO_2 equivalent emissions per 100 kilometers. Panel b) plots the ATT across co-occurrence bins. The underlying data for each of the two panels are the aggregate emission rates for each city, two-hour bin, and (where relevant) co-occurrence group. Panels c) and d) document the treatment effect on ambient fine particulate ($PM_{2.5}$) concentrations as measured by PurpleAir monitors inside and outside of the CBDs of NYC and control cities. Shaded areas and vertical lines denote 95% confidence intervals, with standard errors clustered at the city-level.

5 The Fundamental Traffic Flow Diagram

Two ingredients underlie changes in road speeds on a given segment: 1) changes in traffic volumes, and 2) the congestion function, which maps the density of cars on a road segment to a corresponding speed. This relationship between density and speeds—often referred to as part of the "Fundamental Traffic Flow Diagram"—has long been used by traffic engineers to evaluate the effects of past and potential changes to traffic flows (Greenshields et al., 1935; Greenberg, 1959; Seo et al., 2017). Each road segment has its own congestion function, which may vary across segments based on its physical characteristics (e.g., width, curvature, lane structure, etc.) and typical driving behavior (e.g., spacing between cars). Intuitively, a curvy road full of potholes will operate at slower speeds for a given density of cars than a well-maintained highway.

We estimate a congestion function for six of the primary entrances into the CBD using samples of simultaneous speeds v_s (in miles per hour) and densities ρ_s (in vehicles per mile). We cannot directly observe density, so we infer it by assuming a constant scaling factor on observed aggregated traversals and normalizing relative to the maximum for the road. For a given road, we fit the following functional form from the *Bureau of Public Roads* (BPR):

$$\frac{1}{v_s} = \begin{cases} \frac{1}{v_{\text{FF}}} & \text{if } \rho_s < \rho_{\text{crit}} \\ \frac{1}{v_{\text{FF}}} + c \cdot \left(\frac{\rho_s}{\rho_{\text{crit}}} - 1\right)^{\lambda} & \text{otherwise} \end{cases} \tag{5}$$

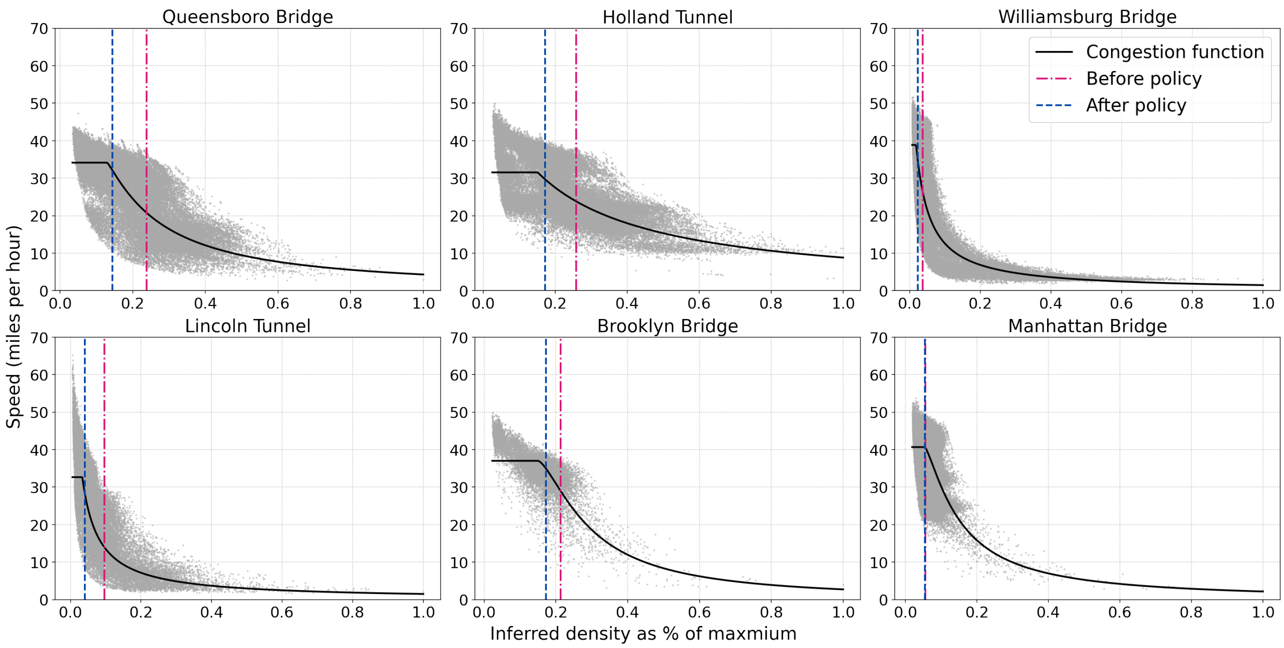
Under this functional form, a segment operates under *free-flow* with speed v_{FF} for all densities $\rho < \rho_{\text{crit}}$. Once the density of vehicles on the segment exceeds the threshold ρ_{crit}, the segment speed slows down at an exponential rate with rate λ. The congestion function for any given road is governed by the three parameters: ρ_{crit}, c, and λ.

Figure 5 shows the fitted congestion functions at each CBD entrance. To illustrate the changes in speeds observed at each entrance, we plot vertical lines for the average normalized density at 3pm before NYC implemented congestion pricing (in pink dashes) and after January 5th, 2025 (in blue dashes). As the figure shows, average speeds doubled in the Lincoln Tunnel, increased by over 50% on the Williamsburg Bridge and the Queensboro Bridge, increased by 25% on the Holland Tunnel, increased by 21% on the Brooklyn Bridge, and were unchanged on the Manhattan Bridge. These speed changes depend on the extent to which traffic along each CBD entrance decreased after January 5th and the convexity of the congestion function at the point of density before January 5th. Although normalized densities on the Holland Tunnel and Queensboro dropped by a similar amount following the implementation of congestion pricing, speeds on the Queensboro Bridge increased by 5 mph more than in the Holland Tunnel. This difference arises because the Queensboro Bridge's congestion function was steeper at the average density before January 5th than that of the Holland Tunnel.

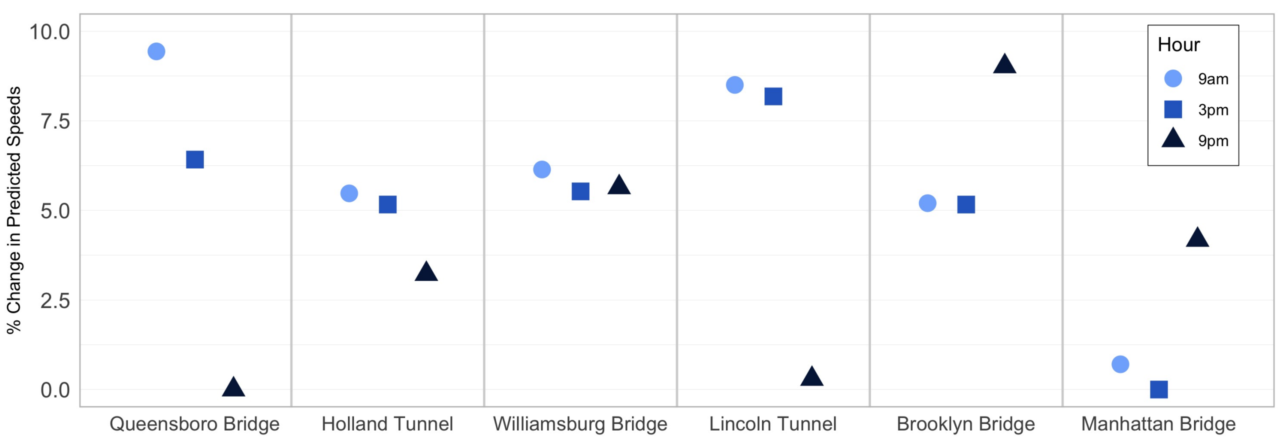
Once estimated, examining a road's congestion function also allows for a *prediction* of how speeds might respond to future policy changes that further reduce the number of cars on the road. In Figure 5 Panel b), we compute the predicted change in speeds corresponding to a further 10% decrease in vehicle density from the post-policy average inferred density at three times of day for all six entrances. The Holland Tunnel and Williamsburg Bridge have similar predicted increases across times of day, ranging from about 3-6%. Predicted speed changes on the Queensboro Bridge, Lincoln Tunnel, Brooklyn Bridge and Manhattan Bridge vary significantly by time of day. In the mornings, the Queensboro Bridge and Lincoln Tunnel operate at a steep part of their congestion functions, so further reductions in density have a large effect on speeds. However, by 9pm, both entrances are already operating near free-flow. The Manhattan Bridge also operates near-free flow at both 9am and 3pm such that the 10% decrease in density has only marginal effects on predicted speeds. By contrast, both the Manhattan Bridge and Brooklyn Bridge have room to grow at 9pm, at which a further 10% decrease in density would increase speeds by 4 percentage points more than at 9am or 3pm.

Figure 5: Congestion functions for CBD entrances

(a) Estimated congestion functions



(b) Predicted change in speeds given 10% further decrease in density (post-policy)



Notes: Panel a) plots the estimated congestion function for road segments along six of the primary entrances into the CBD. Vertical lines correspond to average inferred densities at 3pm before and after the implementation of congestion pricing. The black line is the congestion function, which follows Equation (5) and is fit on observations of speeds and densities for each entrance. A sample of the underlying observations is shown as gray dots. Panel b) plots the change in speeds predicted by a 10% decrease in density. Each point corresponds with the intersection of the congestion function for a fixed change in density starting from the average post-policy density level for a given hour of day (e.g., 9-10am). Figure B.4 provides a map of the road segments corresponding to each entrance.

6 Distributional Effects

Proposals to implement congestion pricing often face concerns over potential adverse impacts on specific groups, such as lower-income drivers (Ecola and Light, 2009; Taylor, 2010). In this section, we estimate the effects of congestion pricing on regions of different income levels, distance to the CBD, and for specific areas of interest such as New Jersey and the Bronx. Table 1 documents the policy's treatment effects on four outcomes for each geographic breakdown, following the same generalized synthetic control methodology as in previous sections. The first two columns show the effects on segments *within* the specified region. The latter two show the effects on speeds for trips *originating* from the region to destinations either inside or outside the CBD.

Median household income. We first compare the effects of the policy on areas with higher or lower income. We divide Census tracts based on where they fall in the within-CBSA distribution of median household income in the 2018-2023 American Community Survey (ACS). Median household incomes in the NYC metro area range from approximately $44,500 for the average tract in the bottom quintile of the distribution to $182,000 for the average tract in the top quintile.

We find that congestion pricing has had broadly similar effects on areas across the income distribution. Our estimates suggest that the positive effects on speeds have been greatest in the *bottom* quintile of income and decreased monotonically as we move up the income distribution, although the differences are small and not statistically significant. The corresponding effect on CO_2 emission rates follows a similar pattern, with the largest decreases for segments in the lowest income tracts. Trips traveling to the CBD from any income quintile have experienced an 8-9% increase in speeds, with no significant differences in effects across quintiles. Trips traveling to destinations outside of the CBD have experienced only slight and insignificant changes in speed, regardless of the income quintile in which they originate.

Distance to the CBD. We next look at effects of the policy on Census tracts that are nearer or farther from the CBD. As expected, the effects are concentrated on tracts closer to the CBD. For tracts in the first quintile—which are an average of 2.4 miles from the CBD—the policy increased speeds on segments within the tracts by 3% and increased speeds on trips to the CBD by 9.3%. The effects on speeds for segments within these tracts and on speeds for trips to the CBD decrease monotonically for tracts farther from the CBD. For tracts in the top quintile—which are an average of 47 miles from the CBD—speeds on segments within the tracts increased only marginally and there are insufficient trips to the CBD to even estimate the effect on their speeds. Effects on CO_2 emission rates and on speeds on trips outside the CBD are small across all distances from the CBD.

Specific regions of interest. Finally, we look at how the policy effect specific regions that garnered significant interest in the lead up to the launch of congestion pricing. While New Jersey policymakers were among the most vocal critics of congestion pricing (Tully and Ley, 2025), we estimate that the policy increased speeds on segments within the two New Jersey counties closest to NYC—Hudson and Bergen—by 3% and decreased the emission rate on these segments by almost 1%. The policy has also increased speeds on trips to the CBD by about 8% for New Jersey drivers from these two counties, with no change in speeds for trips ending outside of the CBD. The policy has similarly impacted the speeds and trip times faced by Long Island residents, although the magnitudes are smaller.

The story for residents of the Bronx is more complicated. We estimate that the implementation of congestion pricing had negative spillovers on speeds for drivers on segments within the Bronx, reducing the average speed by about 2.5%. This decrease in segment-level speed has a corresponding effect on trip-level speeds for trips originating in the Bronx and to destinations outside of the CBD, decreasing their speeds by 3.7%. However, part of this decrease can likely be accounted for by a change in the composition of segments traveled, from faster highways to slower local and arterial roads. When we instead estimate the effects on Bronx speeds split by each type of road, we find no significant evidence of a negative impact on any one road type (Figure B.5). In addition, we find that the policy reduced CO_2 emission rates across the board in the Bronx by 0.5% and increased the speeds on trips to the CBD originating in the Bronx by 4.5%.

Table 1: Distributional effects of congestion pricing

	Segment outcomes (logged) (for segments within region)		**Avg trip speed (logged)** (for trips originating in region)	
Region characteristics	Avg speed	Avg emission rate	To CBD	To outside of CBD
Median income				
0-20th percentile	0.0173	-0.0046	0.0842	0.0063
	(0.0036)	(0.0007)	(0.0132)	(0.0052)
20-40th percentile	0.0154	-0.0032	0.0943	0.0061
	(0.0037)	(0.0007)	(0.0142)	(0.0049)
40-60th percentile	0.0149	-0.0023	0.0931	0.0052
	(0.0035)	(0.0008)	(0.0141)	(0.0049)
60-80th percentile	0.0142	-0.0023	0.0811	0.0059
	(0.0038)	(0.0008)	(0.0134)	(0.0046)
80-100th percentile	0.0137	-0.0021	0.0837	0.0040
	(0.0036)	(0.0009)	(0.0149)	(0.0044)
Distance to CBD				
0-20th percentile	0.0306	-0.0030	0.0924	0.0101
	(0.0067)	(0.0023)	(0.0142)	(0.0067)
20-40th percentile	0.0220	-0.0007	0.0687	0.0039
	(0.0050)	(0.0014)	(0.0143)	(0.0070)
40-60th percentile	0.0213	-0.0041	0.0626	0.0057
	(0.0039)	(0.0014)	(0.0088)	(0.0059)
60-80th percentile	0.0110	-0.0025	0.0603	0.0095
	(0.0043)	(0.0008)	(0.0073)	(0.0047)
80-100th percentile	0.0087	0.0006	–	0.0066
	(0.0040)	(0.0011)		(0.0050)
Specific regions				
Hudson and Bergen counties, NJ	0.0302	-0.0093	0.0818	-0.0006
	(0.0049)	(0.0009)	(0.0068)	(0.0065)
Bronx, NY	-0.0247	-0.0054	0.0442	-0.0366
	(0.0075)	(0.0015)	(0.0090)	(0.0109)
Long Island, NY	0.0252	-0.0047	0.0447	0.0106
	(0.0050)	(0.0009)	(0.0199)	(0.0065)

Notes: This table reports the average treatment effects for different subsets of data, each based on characteristics of the Census tract from within which a segment lies or trip starts. The result for trips to the CBD for the 80-100th percentile of distance are unavailable as there are too few trips from that distance to measure speeds reliably. Standard errors are presented in parentheses.

7 Conclusion

The implementation of congestion pricing in New York City has produced significant short-run effects on traffic conditions, travel times, and estimated emission rates across the metropolitan area. Our findings indicate that speeds within the CBD increased by 16% in the first two months after the policy was implemented, leading to an 8% reduction in average travel times for trips to and within the CBD. These speed increases translate to decreases in vehicle CO_2 emission rates. Congestion pricing has had no statistically significant impact on local air quality, although the estimates are imprecise and could admit economically significant effects.

Beyond the toll zone, we observe substantial spillovers on major CBD entry points and other road segments with high co-occurrence levels. Furthermore, the distributional effects of the policy appear relatively balanced across income groups, with no evidence of disproportionate burdens on lower-income neighborhoods. The primary determinant of congestion relief and emissions reductions is proximity to the CBD, with the greatest increases to speed observed in areas closest to the CBD. The observed changes in speed depend not only on the number of vehicles deterred by the price to enter the CBD, but also the steepness of the congestion function at the relevant points. As prices to enter the CBD increase in future years (MTA, 2024), our estimated congestion functions provide a method for predicting how any further reductions in CBD entries might translate into increased speeds on different entrances.

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Appendices

A Data Appendix

A.1 CBD Definitions

Table A.1 contains references to the CBD definitions we use for the control cities and New York City. Each links to a snapshot of the corresponding web page on the Internet Archive. This avoids links breaking due to website changes of the city-affiliated organizations from which we derive the CBD definitions.

A.2 Measure of co-occurrence

Figure A.1 maps road segments by their level of co-occurrence with the CBD. We exclude the 0-10% range from the lowest bucket as it includes all other road segments not shown.

A.3 Estimating fuel efficiency

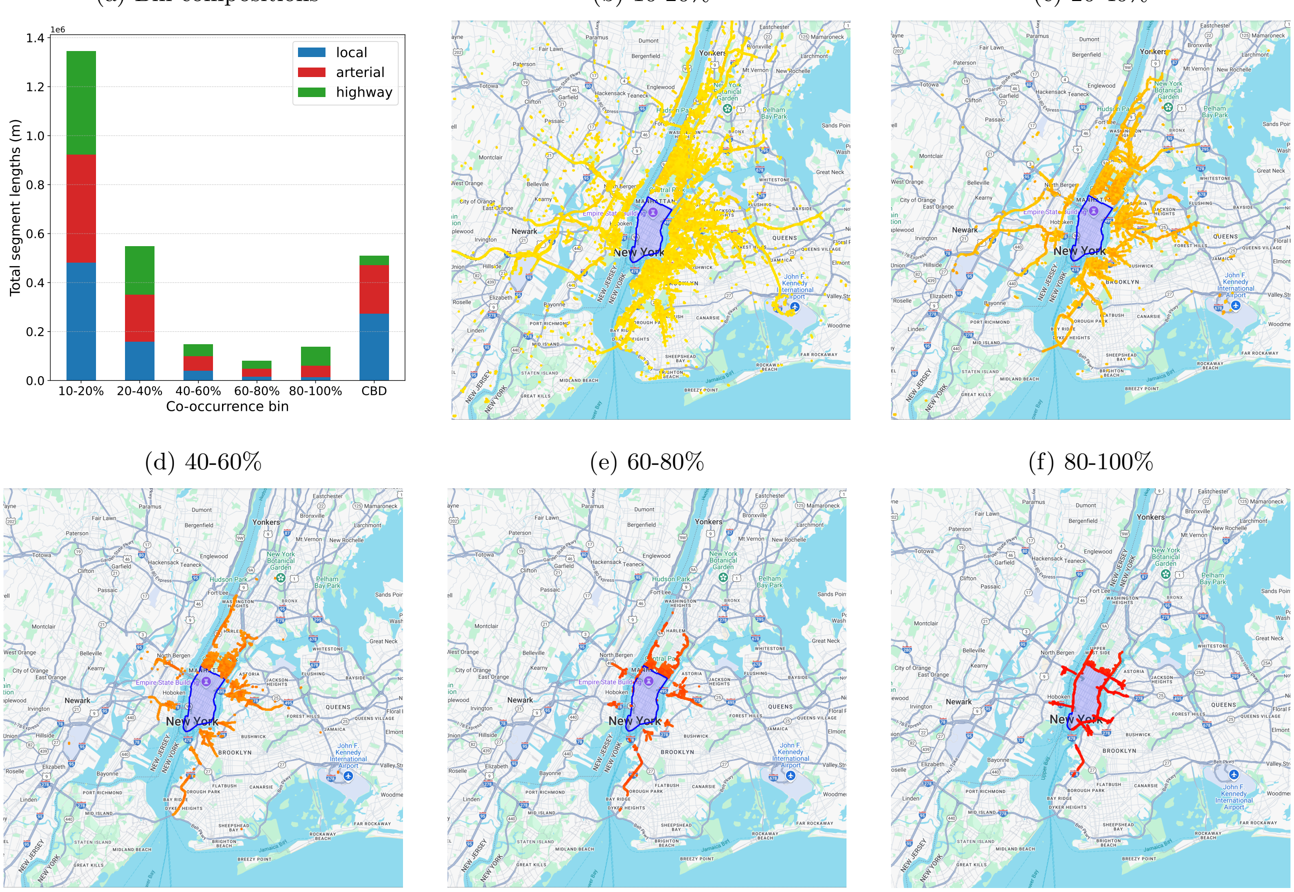
We evaluate the environmental impact of this experiment by measuring fuel consumption rates on road segments. CO_2 emission rates then naturally arise from these estimates of fuel consumption, as carbon emissions are typically modeled as proportional to the fuel consumption in transportation settings (Department for Energy Security and Net Zero, 2023). Since direct measurements of fuel or CO_2 emissions are impractical, we use scalable methods for estimating fuel consumption rates instead.

Fuel consumption modeling has been widely studied in the literature (Faris et al., 2011). Models of this form roughly fall into two categories: principled models (Faris et al., 2011), which aim to model the physics underlying energy usage, and empirical models (Department of Energy , DOE; Ersal et al., 2012; Department of Energy , DOE), which fit often non-parametric models to ground-truth fuel consumption data. For this study, we collaborate with *National Renewable Energy Laboratory* (NREL), integrating their models which fall roughly under both categories. These models at their core rely on FASTSim (Brooker et al., 2015), a physics-based simulator (hence a principled model) which 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 labs (e.g., Argonne National Laboratory), so this is a high-fidelity model with many parameters to calibrate towards 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 NREL's RouteE model (Holden, Reinicke and Cappellucci, 2020). 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 takes 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.

Table A.1: CBD Definitions Overview

Link	City name	Defined by	CBD shape
🔗	Atlanta	Atlanta Downtown	The "Downtown Boundary".
🔗	Baltimore	Downtown Partnership of Baltimore	The "Downtown Management Authority" shape on page 5.
🔗	Boston	City of Boston	The outline of the "Downtown" neighborhood.
🔗	Charlotte	Charlotte Center City Partners	The outline of the "Uptown" area.
🔗	Chicago	City of Chicago	The "Downtown Zone Area".
🔗	Cincinnati	Downtown Cincinnati	The darkest shaded shape, the outline of the "CBD".
🔗	Dallas	Downtown Dallas Inc.	The outline of the "Downtown Improvement District".
🔗	Minneapolis	Downtown Minneapolis Neighborhood Association	The outline of the union of the "Downtown East" and "Downtown West" areas.
🔗	New York City	Metropolitan Transportation Authority	The outline of the "Congestion Relief Zone".
🔗	Philadelphia	Center City District Philadelphia	The boundaries of the district on page 8.
🔗	Phoenix	City of Phoenix	The boundaries of the "Proposed Central Business District".
🔗	Portland	City of Portland	The outline of the "Downtown" area.
🔗	Washington, D.C.	DC Department of Transportation	The outline of the shaded area.

Figure A.1: Segments by bins of co-occurrence



(a) Bin compositions

(b) 10-20%

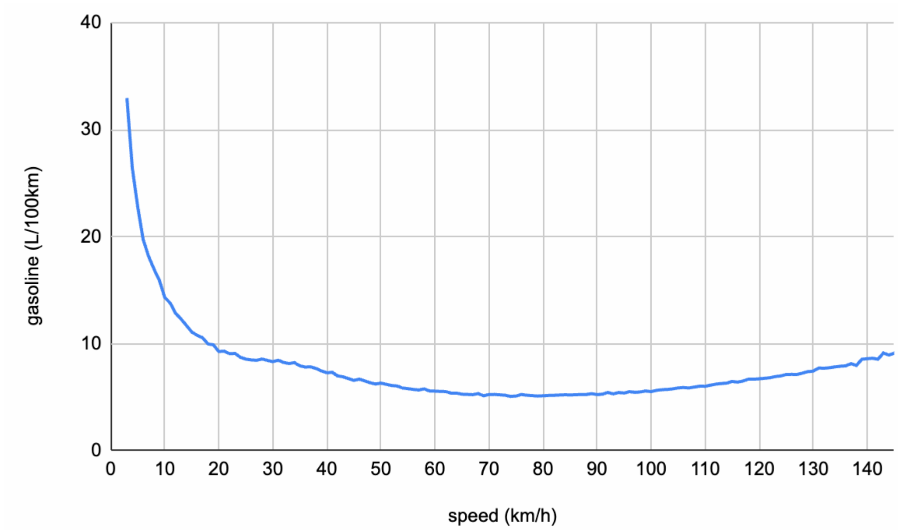
(c) 20-40%

(d) 40-60%

(e) 60-80%

(f) 80-100%

Figure A.2: Example speed-fuel consumption rate curve

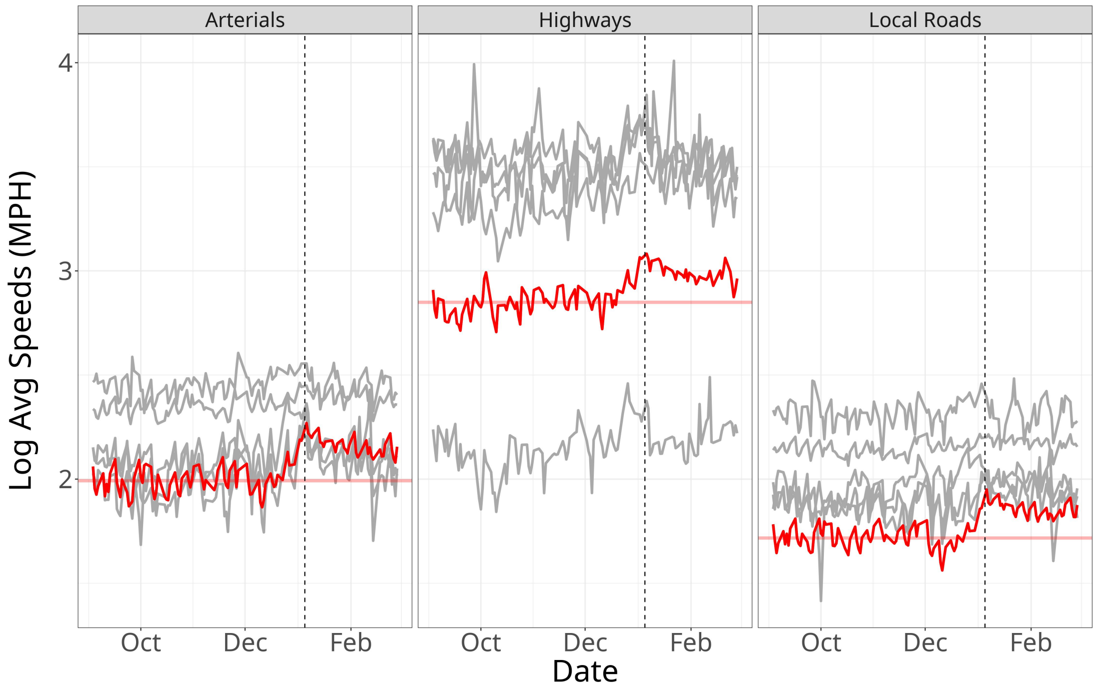


Notes: This figure documents an example of the empirical relationship between speeds and fuel consumption for one class of roads. Similar data are used to model the overall relationship on various roads and road conditions.

Figure A.2 depicts the empirical relationship between speed and fuel consumption on one class of roads, which is used to model the overall relationship. 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.

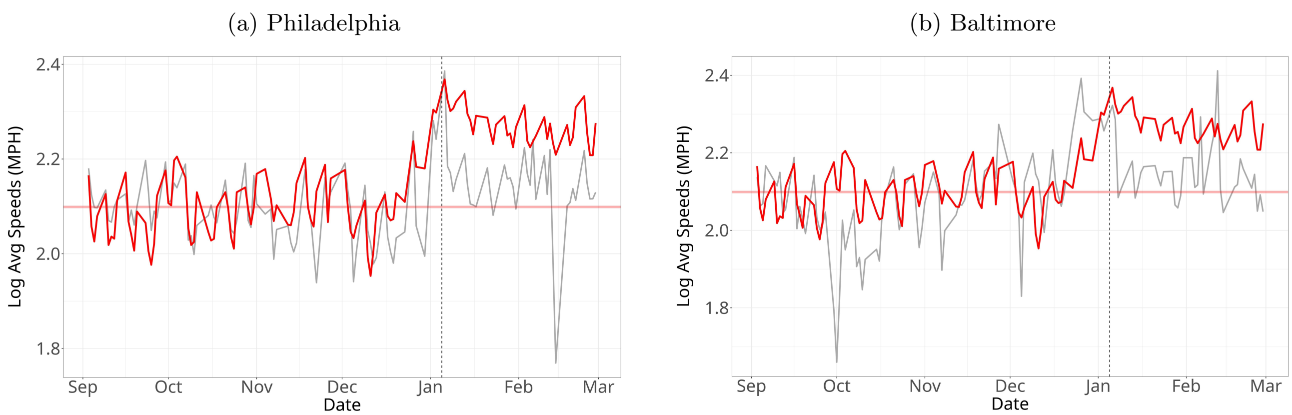
B Supplementary Tables and Figures

Figure B.1: Average CBD speeds by road type



Notes: This figure documents log average speeds on roads in the CBDs of NYC and our set of control cities. The horizontal red line indicates the average of NYC speeds between September 1 and December 15, 2024.

Figure B.2: Average CBD speeds: NYC, Philadelphia, and Baltimore



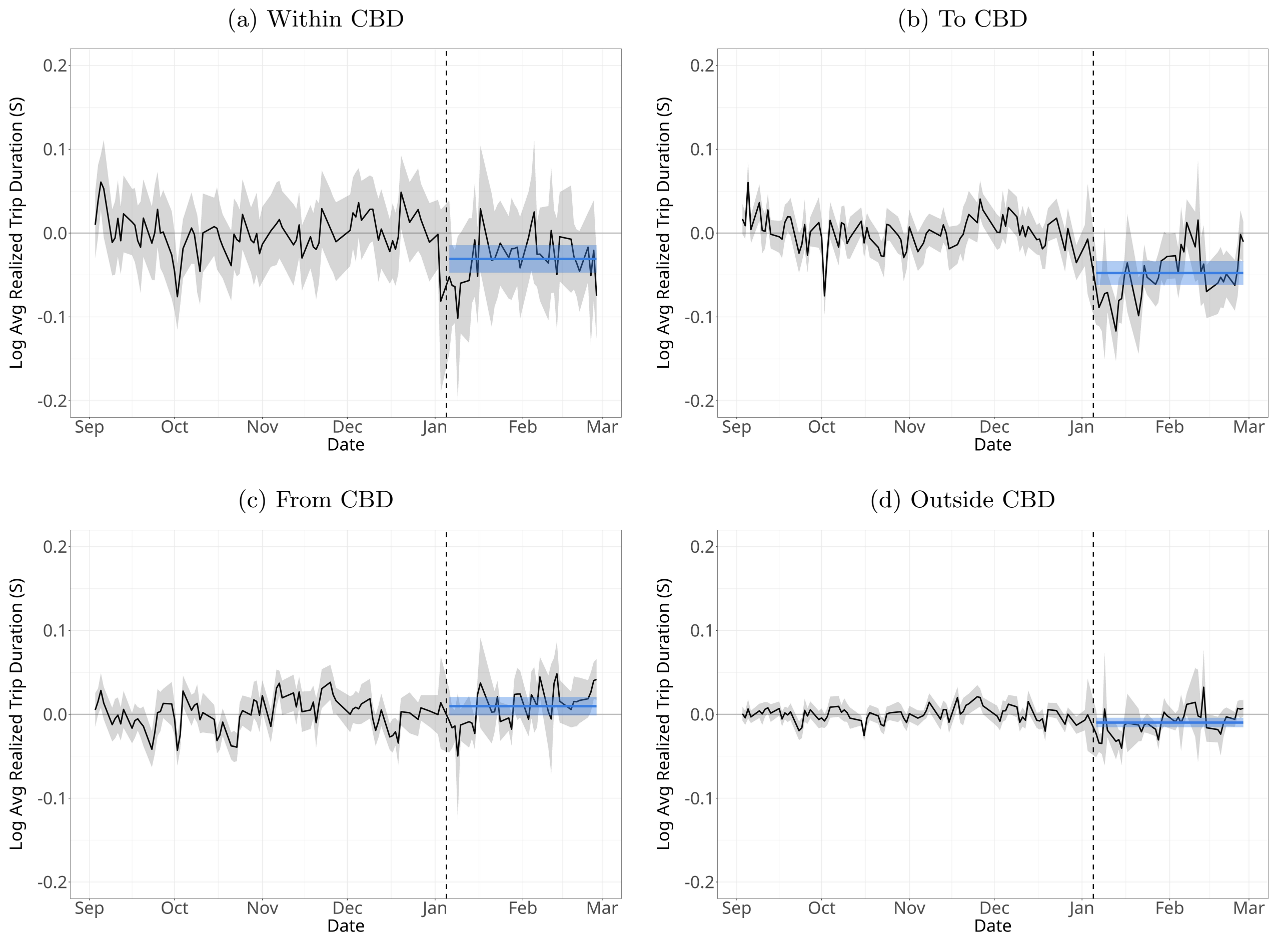
Notes: This figure recreates Panel a) of Figure 1, zooming in on just Philadelphia or Baltimore to provide a clear head-to-head comparison.

Table B.1: Average CBD speeds before and after congestion pricing

		Average speeds (mph)	
City	Road type	Before Jan 5, 2025	After Jan 5, 2025
Atlanta	All	24.25	25.7
	Highway	33.64	34.85
	Arterial	11.64	11.56
	Local	10.12	10.07
Baltimore	All	7.99	8.59
	Highway	8.46	9.09
	Arterial	8.08	8.71
	Local	7.08	7.34
Boston	All	17.57	22.56
	Highway	31.58	34.03
	Arterial	6.99	7.84
	Local	6.48	7.12
Chicago	All	15.83	17.91
	Highway	27.15	30.36
	Arterial	10.45	10.95
	Local	8.53	8.82
New York	All	8.16	9.69
	Highway	17.27	19.85
	Arterial	7.33	8.67
	Local	5.57	6.39
Philadelphia	All	8.08	8.53
	Highway	35.82	35.71
	Arterial	7.9	8.35
	Local	6.47	6.81

Notes: This table reports the average volume-weighted speeds on segments in each of the cities used throughout our analyses for weekday peak hours. The "before" period data starts September 1st, 2024 and the "after" period data ends on February 28th, 2025.

Figure B.3: Treatment effect on trip durations

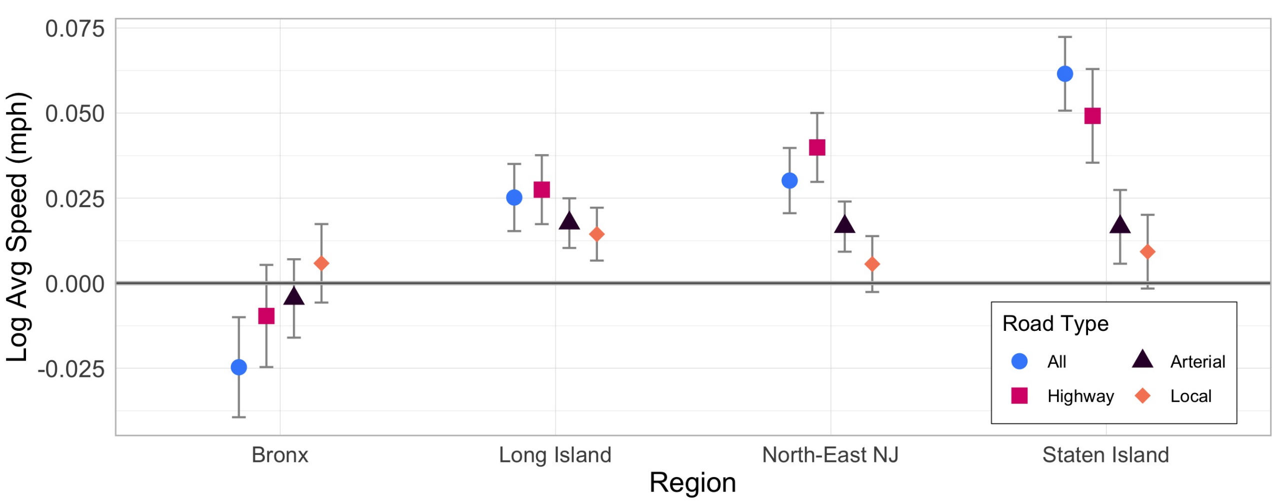


Notes: This figure documents day-level ATT on average realized trip durations split by whether the trip starts and/or ends in the CBD. The underlying data are the aggregate speed for each city, OD type, and two-hour bin. The horizontal blue lines are the aggregate ATTs for all post-treatment periods. Shaded areas represent 95% confidence intervals. Standard errors are clustered at the city-level.

Figure B.4: CBD entrances road segments

Notes: This figure maps the road segments corresponding to the entrances to the CBD used for Figure 5.

Figure B.5: Treatment effect on speeds by region-road type



Notes: This figure documents treatment effects split by levels of region and type of road segment. Each point is separately estimated using the average speeds in two-hour bins for segments with the corresponding level of co-occurrence and road segment type for both NYC and the comparison cities. Vertical bars represent 95% confidence intervals. Standard errors are clustered at the city-level.