Development and validation of a method to quantify benefits of clean-air taxi legislation

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Abstract

Air pollution from motor vehicle traffic remains a significant threat to public health. Using taxi inspection and trip data, we assessed changes in New York City’s taxi fleet following Clean Air Taxi legislation enacted in 2005–2006. Inspection and trip data between 2004–2015 were used to assess changes in New York’s taxi fleet and to estimate and spatially apportion annual taxi-related...
exhaust emissions of nitric oxide (NO) and total particulate matter (PM$_T$). These emissions changes were used to predict reductions in NO and fine particulate matter (PM$_{2.5}$) concentrations estimates using data from the New York City Community Air Survey (NYCCAS) in 2009–2015. Efficiency trends among other for-hire vehicles and spatial variation in traffic intensity were also considered. The city fuel efficiency of the medallion taxi fleet increased from 15.7 MPG to 33.1 MPG, and corresponding NO and PM$_T$ exhaust emissions estimates declined by 82% and 49%, respectively. These emissions reductions were associated with changes in NYCCAS-modeled NO and PM$_{2.5}$ concentrations ($p<0.001$). New York’s clean air taxi legislation was effective at increasing fuel efficiency of the medallion taxi fleet, and reductions in estimated taxi emissions were associated with decreases in NO and PM$_{2.5}$ concentrations.

Introduction

Air pollution from combustion sources such as motor vehicles remains an important threat to public health in many major cities, increasing the risk and severity of cardiovascular and respiratory diseases in adults and children.$^1,2,3$ To address this issue the New York City government has passed a broad series of laws intended to reduce air pollution. Between 2003 and 2011, the city introduced legislation to address multiple emissions sources, including heating oils, city vehicles, buses, trucks, and taxicabs.$^4$ Since the start of data collection in 2008–2009, the New York City Community Air Survey (NYCCAS) has documented meaningful reductions in the concentrations of several key air pollutants in the city,$^5$ which may be partially attributable to these policies.

Because a large set of laws was passed in a short period of time, and because all were implemented against a complex background of higher-level policies and market dynamics that could affect emissions separately from city government action, it is challenging to evaluate the individual effects of each category of clean-air legislation. Similar studies seeking to attribute air pollution changes to specific policy changes often struggle to disentangle the effect of the policy in question from longer-term trends operating on regional or national scales, and may need to measure and adjust for long-term trends or use unaffected cities as control groups.$^6$ An alternative strategy for estimating the impacts of specific policies is to closely map the relevant changes attributable to a specific policy and estimate the pollution reductions associated with that change as spatially apportioned across the city. This strategy enables both the estimation of pollution changes attributable to each initiative as well as the identification of any areas in the city where health impacts could be expected. Further, by using high-resolution air pollution data to analyze intra-city differences rather than overall trends, this approach limits the threat of confounding by time. By making the unit of analysis a grid cell within a city rather than the city itself, any potential confounders would need to vary across the city as well as covary with both the exposure and with overall pollutant concentrations.

In 2005 and 2006, the city passed several laws to reduce emissions from the taxi fleet. Local law 2005/072 directed the Taxi and Limousine Commission (TLC) to approve one or more hybrid vehicle models for use as taxicabs,$^7$ 2006/018 mandated that at least 9% of new medallions sold be restricted to hybrid or compressed natural gas vehicles,$^8$ and 2006/052
incentivized the purchase of low-emission taxicabs by extending the useful lifetime of taxi models that are classified as “clean air” vehicles by the United States Environmental Protection Agency (EPA). This legislation applies to the city’s medallion taxi fleet (also known as “yellow cabs”), but does not apply to so-called “for-hire vehicles.” For-hire vehicles, including traditional car services and rideshare services such as Uber and Lyft, also carry passengers for a fare, but generally cannot legally accept street hails and are subject to a different regulatory system.

This study characterizes changes to the taxi fleet composition and maps corresponding exhaust emissions changes in the context of legislative change targeting medallion taxis. Exhaust emissions of nitric oxide (NO) are considered because NO is a primary pollutant that is an important contributor to the generation of ozone; thus it is both measurable close to the emissions source and has downstream health consequences as a result of ozone creation. Exhaust emissions of total particulate matter (PM$_T$) are considered because of the strong evidence of the respiratory and cardiovascular risk posed by particulate matter air pollution. The for-hire vehicle fleet is used as a comparison group to distinguish the contribution of legislation targeting medallion taxis from the contribution of other time trends in livery vehicle fuel efficiency. Spatial and time trends in emissions from the taxi fleet are considered alongside air pollution data from the New York Community Air Survey in 2009 and 2015. This study seeks to gain an understanding of the taxi fleet’s contribution to overall air pollution reduction and to identify areas in the city that may have been especially affected by the taxi legislation, providing information about exposure that can be used in future health impact studies.

**Methods**

This study estimates temporal and spatial trends in taxi fleet NO and PM$_T$ exhaust emissions. The total exhaust emissions of the fleet are estimated for each year 2004–2015. For the years 2009–2015, the date range in which both NYCCAS and taxi inspection data are available, emissions estimates are allocated over a map of New York City with a 300-meter resolution. These emissions estimates are then compared to NO and fine particulate (PM$_{2.5}$) NYCCAS raster surfaces estimated from land-use regression models to evaluate how taxi fleet exhaust emissions changes were associated with overall spatial and temporal trends in air pollution in New York. Although PM$_T$ and PM$_{2.5}$ are not equivalent pollutants, PM$_{2.5}$ is a component of PM$_T$, and particulate emissions from light-duty gasoline vehicle exhaust are primarily fine particles.

Annual emissions estimates were calculated through a three-step process. First, the fleet composition in each year was determined by finding the numbers of each model of car used as a taxi in that year. Second, the annual vehicular miles travelled (VMT) for the fleet were calculated, stratified by vehicle model and model year. Third, the exhaust emissions for the fleet were estimated by summing the VMT for each vehicle model multiplied by that vehicle’s estimated fuel consumption and a fuel-based emissions factor. This figure for total emissions was allocated over a grid with 300-meter resolution using spatial data from the TLC’s public trip data set.
NYCCAS Monitoring

The methodology of NYCCAS have been described in detail elsewhere.\textsuperscript{9,13} Briefly, data from about 100 monitoring sites were used to develop a land-use regression model that predicts local air pollution levels throughout New York City from land use characteristics. Validation sites showed that the model differed from measured pollution levels by 9.9\% (mean absolute percent error) for fine particles and 18.4\% for nitrogen dioxide.\textsuperscript{9} NYCCAS 300-meter-resolution annual average raster surfaces for NO and PM$_{2.5}$ in 2009 and 2015 were used examine the spatial and temporal relationship between trends in taxi emissions and related pollution in New York.

Fleet Composition

The composition of the medallion taxi fleet was determined from a data set of medallion taxi inspections obtained via a Freedom of Information Law (FOIL) request from the TLC. Medallion taxis must pass inspection three times per year, and at each inspection the medallion license number, vehicle make and model, and odometer reading are recorded. The inspection data used in this study include all inspections from December 2003 until December 2015.

To assess the vehicle make and model composition in year, the number of unique medallion IDs for each model/model year combination were counted. This method results in an overestimation of the size of the vehicle fleet in any year, because new vehicles keep the same medallion number. Therefore, the raw counts were linearly scaled down to a fleet size equal to the number of active licenses recorded in the TLC’s annual report for the year.

Comparison with the For-Hire Fleet

The for-hire fleet was not impacted by the local legislation targeting medallion taxis. However, hybrid vehicles can be cheaper to operate as livery vehicles than less efficient conventional vehicles,\textsuperscript{14} so hybrids may have replaced conventional vehicles in the for-hire fleet even without explicit policy initiatives. Comparing changes to the Department of Energy-provided fuel efficiencies of the medallion taxi and for-hire fleets therefore enables an understanding of the contribution of the clean-air taxi legislation to changes in the medallion taxi fleet beyond what might be expected due to market forces alone.

The characterization of the makeup of the for-hire fleet in each year used the same approach described above, adapted to annual inspection data of for-hire vehicles obtained via FOIL request from the TLC. These data include the vehicle identification number (VIN), make, license plate, and odometer reading for all annual for-hire vehicle inspections between 2009 and 2015. Vehicle model/year was identified by decoding each vehicle’s VIN number.\textsuperscript{15}

Vehicular Miles Travelled

Per-model and fleet VMT were calculated from taxi inspection data adapting the method described by Wilson et al.\textsuperscript{16} The full inspection dataset was used to create unique “intervals.” Each interval includes data from two consecutive inspections of the same vehicle. For each interval, the daily mileage rate was calculated by dividing the difference in
odometer readings by the number of days between the two inspections. Intervals were used to calculate VMT, subject to the following four data quality criteria:

1. Intervals with a 0 odometer reading for the second inspection of the interval were excluded.
2. Intervals where the second odometer reading is lower than the first were excluded.
3. Intervals with less than 15 days between inspections were excluded. A short interval likely indicates that the taxi failed its inspection and was reinspected (often on the same day), and this period is not likely to reflect typical VMT.
4. Remaining intervals with a mileage rate greater than 1,000 miles per day were assumed to be data errors, as this is would represent an implausible scenario for urban driving. These intervals were not deleted, but their calculated mileage rates were replaced with 1,000 miles per day to limit the influence of extreme outliers.

Of 634,407 intervals initially created, 265,452 were eliminated due to the data quality criteria, leaving 368,955 intervals for further analysis. 2,548 of these intervals (0.69%) were reduced to 1,000 miles/day.

To estimate mean miles travelled for each vehicle model, the fifteenth of January, May, and September were chosen as observation dates for each year between 2004 and 2015 in order to sample evenly across each year without artificially increasing the sample size above 3 inspections per year. At each of these dates, the mean miles per day of all intervals that straddled that day was calculated, stratified by vehicle model/year. The mean miles per day across all three observation dates in every year was then calculated for each vehicle model/year along with a pooled standard error term. This results in the mean miles per day travelled by taxis of each model/year in every year 2004–2015.

Finally, the vehicular miles travelled for each vehicle model/year were calculated by multiplying the estimated distance per day by the number of days in that year and the number of taxis of that model/year.

### Emissions

Exhaust emissions from the taxi fleet in each year were estimated using fuel-based emissions factors. May et al. report a fuel-based exhaust emissions factor inventory for in-use light-duty gasoline vehicles from model years between 1987 and 2012. These vehicles are classified based on the EPA emissions regulations that applied during that vehicle’s model year. Pre-LEV (low-emissions vehicle) cars were manufactured before 1994; LEVI between 1994–2003; and LEV2 in 2004 or later. From the May et al. cold-start test data, mean emissions factors for NO and PM$_T$ for all three model-year categories were calculated. A specific fuel-based emissions factor for PM$_{2.5}$ was not available, so PM$_T$ was used as a proxy.

To estimate total exhaust emissions from each vehicle model in each year, the VMT for each vehicle model/model year was multiplied by the inverse of that vehicle’s Department of Energy city fuel economy and the per-gallon emissions factor for the car’s model year and...
the pollutant in question. The exhaust emissions from all vehicle models were summed for each year to estimate the total annual emissions from the fleet. These estimates do not include emissions from non-combustion sources such as brake and tire wear.

**Spatial Allocation of Taxi-Related Emissions**

The TLC’s public taxi trip data set was used to develop maps of taxi traffic intensity across New York City. The trip data include the date, pickup coordinates, and dropoff coordinates of every taxi trip since 2009. A random sample of 25,000 trips was chosen from each month from 2009–2015, as working with the entire data set proved computationally prohibitive and a sample 25,000 trips per month provided adequate stability. The start and stop points were snapped to the closest point on the New York City street network, and Grass GIS version 7.5\(^19\) was used to calculate two potential paths between each pair of start and stop points: the shortest-distance path along the road network and the shortest-time path based on speed limit. On average, the path-finding algorithm was successful for about 98.9% of trips, but failed to find a shortest path between the two points for the remaining 1.1%, and these trips were excluded. These paths were unable to be calculated both because of invalid coordinates in the taxi trip data set and because of some discontinuity in the road network, but are effectively missing at random.

A grid with 300-meter resolution was adapted from NYCCAS pollution raster maps, and the taxi paths were clipped to this grid using the “sf” package\(^20\) in R version 3.5.0.\(^21\) For both shortest-distance and shortest-time paths, the total path distance within each grid cell was summed, and the proportion of total distance within each grid cell was computed. Annual maps for shortest-distance and shortest-time were created by taking an average of the traffic proportion in each grid cell across all months, weighted by the total number of taxi trips in each month. These raster maps with a proportional allocation of taxi traffic across the city were then multiplied by the estimated total mass of NO and PM\(_T\) emitted by the taxi fleet in each year to create maps that showed the allocation of emissions across the city based either on shortest-distance or shortest-time paths. Finally, a difference raster for each pollutant- and path-specific taxi emissions estimate was created by subtracting the 2009 emissions raster from the 2015 emissions raster. The difference raster reflected changes in both total fleet emissions and local taxi traffic intensity. Information on how the composition of the taxi fleet may have varied across the city was unavailable.

**Statistical Analysis**

To assess fuel efficiency differences between the medallion taxi and for-hire vehicle fleets, a two-sided two-sample T-test without an equal variance assumption was used to compare the mean fuel efficiencies of the two fleets in 2015. Linear regression was used to assess an interaction term between year and fleet type to determine whether the taxi fleet’s fuel efficiency changed at a different rate than the for-hire vehicle fleet’s efficiency.

To examine the association between our estimates of changing taxi emissions and overall pollutant concentration changes in New York, we used linear regression to estimate the association of NO and PM\(_T\) emissions changes with NYCCAS-modeled NO and PM\(_{2.5}\) concentration changes within 300mx×300m cells from 2009 to 2015, using raster maps of...
the changes in annual average pollutant concentrations and changes in annual average exhaust emissions estimates between 2009 and 2015. Potential confounding due to other sources of motor-vehicle emissions was addressed using total traffic volume from the New York Metropolitan Transportation Council (NYMTC) Best Practices Model from 2010. While this adjustment does not account for changes to the spatial distribution of traffic emissions, it helps control for any changes in traffic emissions that are proportional to baseline traffic volume. To mitigate spatial autocorrelation of residuals, two distinct modeling strategies were employed: global regression and geographically weighted regression (GWR). The GWR model estimates local parameters for every 300mx300m cell without assuming stationarity, with the contributions to parameter estimates from closer cells weighted more heavily in the model than distant cells. Similar models were computed using emissions estimates from either shortest distance or shortest time maps as the exposure of interest. All models were log-log transformed. The GWR was computed with the “spgwr” package\textsuperscript{22} in R 3.5.0\textsuperscript{19} using a 1-kilometer bandwidth. Traffic volume data was not available in all cells, resulting in differences between overall cell counts and cell counts that contributed to regression models. All code is available upon request of the authors.

Results
Fleet Composition

In 2004, an estimated 11,916 of the total 12,741 licensed taxis (93.5\%) were Ford Crown Victorias with a city fuel economy between 15 and 16 miles per gallon (MPG) depending on model year. By 2015, Crown Victorias had decreased substantially in number and in percentage to 1,207 vehicles (8.9\% of a 13,587-taxi fleet). Crown Victorias were superseded by more-efficient hybrid models, primarily the Toyota Camry Hybrid (5,081 vehicles in 2015, 33–40 city MPG), the Ford Escape Hybrid (2,311 vehicles in 2015, 28–30 city MPG), and the Toyota Prius Hybrid (1,695 vehicles in 2015, 42–54 city MPG).

Fleet Fuel Efficiency and Comparison with the For-Hire Fleet

In 2009, the medallion fleet had a mean city fuel economy of 18 MPG and the for-hire fleet had a mean city fuel economy of 16 MPG. Figure 1 demonstrates that although the fleet fuel efficiency of the medallion and for-hire fleets both increased between 2009 and 2015, the medallion fleet demonstrated greater efficiency improvements. By 2015, the medallion fleet’s city fuel economy had increased to 33 MPG (82.6\% increase) while the for-hire fleet had increased to 21 MPG (29.7\% increase). A two-sided T-test of mean fuel efficiency between both fleets in 2015 shows that this 12-MPG difference is significant (p<0.0001). Linear regression for the years 2009–2015 shows a significant positive interaction term between year and fleet type (p<0.0001), suggesting that the medallion fleet increased its fuel efficiency significantly faster than the for-hire fleet did.

Emissions

While the taxi fleet’s vehicular miles travelled remained stable (±3.3\%) between 2004–2015, estimated exhaust emissions of NO and PM\textsubscript{T} declined substantially, from 7,273 metric tons of NO and 7,668 kg of PM\textsubscript{T} in 2004 to 1,338 metric tons of NO and 3,935 kg of PM\textsubscript{T} in 2015. 79.0\% of the decline in NO emissions occurred between 2004 and 2009, before
substantial taxi fleet changes had occurred, suggesting that an important contributor to changes in NO emissions were the stricter EPA emissions requirements that went into effect for vehicles in model years 2004 and later; thus early NO decreases were likely independent of local policy initiatives. In contrast, 95.9% of the decline in PM$_{T}$ emissions occurred after 2009, suggesting that a major reason for the estimated emissions reductions from 2009 to 2015 was the increased fuel efficiency of the taxi fleet.

Spatial data

Table 1 presents descriptive statistics of estimated taxi exhaust emissions changes 2009–2015 for both NO and PM$_{T}$ for both shortest-distance and shortest-time models at the 300-meter grid cell level. Most cells have estimated reductions in both NO (shortest distance: 69.1%; shortest time: 63.7%) and PM$_{T}$ (shortest distance: 68.9%; shortest time: 63.6%) or had no taxi traffic measured in either year (shortest distance: 20.7%; shortest time: 22.1%).

Table 2 shows the results from regression modeling. In adjusted and unadjusted linear models for both shortest-distance and shortest-time paths, estimated changes in taxi-fleet NO and PM$_{T}$ emissions are significantly associated with NYCCAS NO and PM$_{2.5}$ concentration changes, respectively, although the estimated effect sizes are small. Geographically weighted regression attenuates these results for the shortest-distance NO models, and effectively eliminates the relationships in all other models. Figures 2–9 present maps of taxi fleet NO and PM$_{T}$ emissions changes from the shortest-time model and NYCCAS NO and PM$_{2.5}$ concentration changes. These maps show clear patterning of taxi emissions changes across the city, with a the largest estimated decrease in emissions in midtown and lower Manhattan where taxi traffic is concentrated; this spatial autocorrelation is reflected in the difference between the global and geographically-weighted regressions.

Discussion

Comparing the medallion taxi fleet to the for-hire vehicle fleet provides evidence that New York City’s clean-air taxi legislation was effective in increasing the fuel efficiency of the taxi fleet. However, the medallion taxi fleet accounts for only about 5% of the vehicular miles travelled on New York’s streets. Even in the central business district, taxis and for-hire vehicles combine for less than half of total VMT, and street traffic is just one source of air pollution among many. In addition, the EPA’s 2004 emissions regulations may have done more to reduce taxi NO emissions than the clean-air taxi legislation did. Clean-air taxi legislation was therefore not the only contributing factor to the taxi emissions reductions between 2004–2015, and these reductions in taxi emissions had only a modest, although statistically significant, association with the overall pollution reductions measured by NYCCAS between 2009–2015.

This study was limited in several important ways. First, the use of fuel-based emissions factors was an approximation, and fuel consumption was itself estimated based on fuel economy; real-world driving conditions can result in different fuel consumption and exhaust emission patterns than tests. In addition, increased fuel efficiency does not necessarily lead to decreased exhaust emissions. A measure of actual taxi emissions, such as from tailpipe monitors, would have provided more reliable estimates of how emissions changed over time.
Second, only exhaust emissions were considered, although the majority of particulate matter pollution from road traffic results from non-exhaust processes such as brake, tire, and road wear. These sources do not decline with decreasing exhaust emissions and may even increase in some electrified vehicles.\textsuperscript{26} Third, taxi position was estimated through simplified models of driver behavior that may inaccurately reflect reality. Finally, the spatial allocation of emissions did not include a dispersion model to estimate how primary and secondary pollutants can spread across the city, which could have provided better predictions of where health-relevant pollution changes have occurred. Despite these limitations, this study provides an important foundation for future health impact evaluations of existing New York City emissions reduction strategies.

The focus of this study is on fine-scale intracity variation in emissions and pollution, but emissions sources outside of the city such as power plants and shipping activity can have strong influences on health-relevant pollutants as well, contributing to about half of the particulate matter air pollution in New York.\textsuperscript{27} Because of the spatial resolution of our analysis, such emissions sources are unlikely to have confounded our results, but they are still worth attention. Although the impact of city government action on air pollution may be powerful, its health benefits are ultimately limited to the extent that pollution is generated within city borders.

Reducing urban air pollution is a critical public health goal that requires careful evaluation of the effectiveness of local legislation, and our analysis suggests that New York’s 2005–2006 Clean Air Taxi legislation contributed to reductions in concentrations of health-relevant pollutants. As market changes such as the ascendance of ride-sharing services since 2013 challenge the legal framework of for-hire vehicles and medallion taxis in New York,\textsuperscript{23} a comprehensive understanding of the effects of previous legislation is critical. If legislation similar to the 2005–2006 Clean-Air Taxi laws is applied to the for-hire vehicle fleet, the result could be substantial. At the time of submission, over 111,000 cars were licensed as for-hire vehicles: more than twice as many as in 2013 and more than eight times the current number of medallion taxis. Fuel consumption and emissions reductions in a fleet of this size could have a much greater absolute effect than similar proportional reductions in the smaller taxi fleet. Differential impacts across the city are also worth attention. The greatest emissions reductions in the taxi fleet were found in predominantly-wealthy midtown and lower Manhattan, while the greatest respiratory illness burden is found in poor neighborhoods and in the outer boroughs, suggesting that other types of policies may be necessary to make meaningful advances in improving respiratory health.

Future work can focus on different legislation and different pollution sources. In the same time period as the taxi legislation, city buses and building boilers were also targeted for emissions reform. Burning dirtier fuels than gasoline, these pollution sources may have more meaningful health effects than the taxi fleet: one study modeling the likely effects of banning high-sulfur heating oils estimated that up to 290 premature deaths per year could be averted by that policy.\textsuperscript{28} A comprehensive empirical evaluation of all existing air-quality legislation can help to both determine the health impact of existing legislation as well as provide evidence for how future legislation can best be designed to improve public health.
Our future analyses will assess the effectiveness of these initiatives individually and in combination.

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Figure 1:
Change in fleet fuel efficiency over time, comparing the medallion taxi fleet to the for-hire vehicle fleet. Data is available between 2004–2015 for the medallion taxi fleet and 2009–2015 for the for-hire vehicle fleet.
Figure 2:
Estimated exhaust emissions of nitric oxide from the taxi fleet in 2009. Spatial allocation of emissions is based on shortest-time paths between start and stop points.
Figure 3:
Estimated exhaust emissions of nitric oxide from the taxi fleet in 2015. Spatial allocation of emissions is based on shortest-time paths between start and stop points.
Figure 4:
Changes in estimated taxi exhaust emissions of nitric oxide, subtracting 2009 values from 2015 values. Spatial allocation of emissions is based on shortest-time paths between start and stop points.
Figure 5:
Changes in NYCCAS-modeled nitric oxide concentrations, subtracting 2009 values from 2015 values.
Figure 6:
Estimated exhaust emissions of total particulate matter from the taxi fleet in 2009. Spatial allocation of emissions is based on shortest-time paths between start and stop points.
Figure 7:
Estimated exhaust emissions of total particulate matter from the taxi fleet in 2015. Spatial allocation of emissions is based on shortest-time paths between start and stop points.
Figure 8:
Changes in estimated taxi exhaust emissions of total particulate matter, subtracting 2009 values from 2015 values. Spatial allocation of emissions is based on shortest-time paths between start and stop points.
Figure 9:
Changes in NYCCAS-modeled PM$_{2.5}$ concentrations, subtracting 2009 values from 2015 values.
Table 1:

Cell values of all maps used in regression models (bolded), the base NO and PM$_{2.5}$ concentrations from NYCCAS modeling, the base NO and PM$_T$ taxi exhaust emissions estimates, and 2010 taxi vehicular miles travelled. Taxi data are shown as estimated from both shortest-distance and shortest-time paths.

|                             | $n$ | Mean (SD) | Q1  | Median | Q3  |
|-----------------------------|-----|-----------|-----|--------|-----|
| NYCCAS NO Concentration 2009 (ppb) | 8760 | 22.8 (8.1) | 18.3 | 21.6   | 25.8 |
| NYCCAS NO Concentration 2015 (ppb) | 8760 | 17.2 (5.4) | 14.5 | 16.6   | 19.4 |
| Δ NYCCAS NO Concentration 2009–2015 (ppb) | 8760 | −5.6 (3.2) | −6.4 | −5.1   | −3.7 |
| NYCCAS PM Concentration 2009 (ppb) | 8636 | 10.4 (1.2) | 9.6  | 10.1   | 10.9 |
| NYCCAS PM Concentration 2015 (ppb) | 8760 | 8.5 (1.1)  | 7.8  | 8.3    | 9.1  |
| Δ NYCCAS PM$_{2.5}$ Concentration 2009–2015 (ppb) | 8557 | −1.9 (0.3) | −2.0 | −1.8   | −1.7 |
| NYMTC Total Traffic VMT, 2010 (thousands of miles) | 7287 | 2,470 (3,720) | 343  | 992    | 2,580 |
| Shortest distance Taxi VMT, 2010 (thousands of miles) | 8760 | 108 (502) | 0.1  | 1.5    | 11.6 |
| Taxi NO, 2009 (kg) | 8760 | 294.9 (1,375.0) | 0.2  | 3.9    | 32.6 |
| Taxi NO, 2015 (kg) | 8760 | 152.8 (647.4)  | 0.00 | 2.0    | 18.9 |
| Δ Taxi NO, 2009–2015 (kg) | 8760 | −142.1 (741.2) | −12.5 | −1.6  | 0.0  |
| Taxi PM$_T$, 2009 (kg) | 8760 | 0.9 (4.0)  | 0.0  | 0.0    | 0.1  |
| Taxi PM$_T$, 2015 (kg) | 8760 | 0.5 (1.9)   | 0.0  | 0.0    | 0.1  |
| Δ Taxi PM$_T$, 2009–2015 (kg) | 8760 | −0.4 (2.1) | 0.0  | 0.0    | 0.0  |
| Shortest time Taxi VMT, 2010 (thousands of miles) | 8760 | 108 (471) | 0.00 | 0.63   | 5.50 |
| Taxi NO, 2009 (kg) | 8760 | 294.9 (1,283.9) | 0.0  | 1.7    | 15.6 |
| Taxi NO, 2015 (kg) | 8760 | 152.8 (635.3)  | 0.0  | 0.8    | 9.2  |
| Δ Taxi NO, 2009–2015 (kg) | 8760 | −142.1 (667.5) | −5.8 | −0.7   | 0.0  |
| Taxi PM$_T$, 2009 (kg) | 8760 | 0.9 (3.7)  | 0.0  | 0.0    | 0.1  |
| Taxi PM$_T$, 2015 (kg) | 8760 | 0.5 (1.9)   | 0.0  | 0.0    | 0.0  |
| Δ Taxi PM$_T$, 2009–2015 (kg) | 8760 | −0.4 (1.9) | 0.0  | 0.0    | 0.0  |
Table 2:

All models: n=7,244

|                              | Linear models | Unadjusted<sup>a</sup> | Adjusted<sup>b</sup> |
|------------------------------|---------------|-------------------------|-----------------------|
|                              |               | b<sup>**</sup> (SE)     | b<sup>**</sup> (SE)   |
| Nitric oxide                 |               |                         |                       |
| Shortest distance            |              | 0.25 (0.005)            | 0.25 (0.005)          |
| Shortest time                |              | 0.23 (0.005)            | 0.23 (0.005)          |
| Particulate matter           |               |                         |                       |
| Shortest distance            |              | 0.06 (0.002)            | 0.06 (0.002)          |
| Shortest time                |              | 0.06 (0.002)            | 0.06 (0.002)          |
| Geographically-weighted regressions | Median b<sup>**</sup> (IQR) | Median b<sup>**</sup> (IQR) |
| Nitric oxide                 |               |                         |                       |
| Shortest distance            |              | 0.06 (0.16)             | 0.06 (0.16)           |
| Shortest time                |              | 0.01 (0.13)             | 0.01 (0.15)           |
| Particulate matter           |               |                         |                       |
| Shortest distance            |              | 0.01 (0.07)             | 0.01 (0.07)           |
| Shortest time                |              | −0.01 (0.04)            | 0.00 (0.01)           |

<sup>a</sup> slope of the taxi emissions change term in the regression model

<sup>b</sup> In unadjusted models, the log of estimated taxi emissions changes 2009–2015 in each cell predicts the log of NYCCAS pollution changes (equation below):

\[ \Delta\text{NYCCAS}_{2015–2009} = \log (\max (\Delta\text{TaxiEmissions}_{2015–2009}) - \Delta\text{TaxiEmissions}_{2005–2009} + 0.01) \]

In adjusted models, the log of estimated taxi emissions changes 2009–2015 in each cell predicts the log of NYCCAS pollution changes, controlling for the log of 2010 NYMTC total traffic volume (equation below):

\[ \Delta\text{NYCCAS}_{2015–2009} = \log (\max (\Delta\text{TaxiEmissions}_{2015–2009}) - \Delta\text{TaxiEmissions}_{2005–2009} + 0.01) + \log (\text{TotalVMT}) \]

Because all models are log-log transformed, slopes can be interpreted as a 1% cell-to-cell difference in estimated taxi emissions changes corresponding with a b% cell-to-cell difference in NYCCAS pollutant concentration changes. Shortest-distance models spatially apportion taxi emissions based on shortest-distance paths between pairs of taxi start and stop points, while shortest-time models are based on shortest-time paths using speed limits.