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From Metropolitan Planning Organization to Transport Management Areas: a change of air?

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Abstract

The aim of this study is to investigate policy actions and institutional changes in local governance structures as determinants of air pollutant reductions in US urban areas over the last decade. We adopt regression discontinuity design techniques for the evaluations of pollution reduction policies, exploiting the designation of US Transport Management Areas as a quasi-experimental framework. Results show they provide a governance framework that might facilitate the implementation of policies that reduce traffic congestion and improve air quality.

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1. Introduction

Road traffic is a major contributor to air pollution and greenhouse gas emissions globally (McDuffie et al. (2021) amongst others; for contributions exploiting COVID-19 traffic restrictions, see, for example, Llaguno-Munitxa and Bou-Zeid (2023)). Vehicle emissions, arising from both fuel combustion and non-exhaust sources like engine, brake, tire, and road surface wear, alongside the resuspension of street dust, contribute significantly to particulate matter (PM), nitrogen oxides (NOx), and carbon dioxide (CO2) emissions (European Environment Agency, 2016). These emissions disperse into the ambient air, becoming traffic-related air pollution (TRAP), which degrades air quality.

Exposure to TRAP increases the risk of numerous adverse health effects, ranging from premature mortality and cardiovascular disease to cognitive and metabolic impairments (Fu et al., 2021; Khreis, 2020). Beyond these direct health consequences, there are substantial societal burdens, including increased medical costs, lost school and work days (Nurmagambetov et al., 2018), reduced worker productivity (Chang et al., 2016), and brain drain (Xue et al., 2023).

The majority of human exposure to TRAP occurs in urban areas (Kura et al., 2013). Despite significant improvements in air quality in many Western countries over recent decades, most cities worldwide struggle to meet established air quality standards and guidelines (World Health Organization). Given the projected rapid growth of urban populations globally (United Nations and Department of Economic and Social Affairs Population Division, 2022), an increasing number of people will be at risk of exposure to TRAP.

Considering these factors, this study investigates the impact of policy actions and institutional changes in local governance structures on air pollutant reductions in US urban areas over the past decade, specifically focusing on Transport Management Areas (TMAs). Designated by the US Secretary of Transportation for urbanized areas exceeding a population of 200,000 as defined by the US Census Bureau, TMAs are created to address the complexities of transportation issues. Their overarching goal is to enhance quality of life through safer, more efficient, and environmentally sustainable transportation systems. Due to the requirement to develop long-term transportation plans subject to federal oversight, TMAs receive a larger share of federal transportation funding compared to non-TMA areas. These plans often promote transit-oriented development (TOD), an urban planning strategy designed to reduce reliance on car travel and encourage the use of low-emission vehicles. This approach is expected to lead to a reduction in greenhouse gas emissions and air pollutants (Brownstone and Golob, 2009; Glaeser and Kahn, 2010). Therefore, we utilize the designation of TMAs as a quasi-experimental framework to examine whether the adoption of a more formalized planning approach, emphasizing accountability and responsibility (influenced by the Transportation Equity Act for the 21st Century of 1998 and the Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users of 2005), and the subsequent opportunity for greater funding, leads to a reduction in CO2 emissions.

From a methodological point of view, we rely on Regression Discontinuity Design (RDD) techniques, a long-standing way to obtain credible causal estimates that is gaining increasing popularity in recent times (among others, Cattaneo and Titiunik (2022)).

2. Regression Discontinuity Design

Drawing causal inference about policy effects from observational data presents a significant challenge. Regression Discontinuity Design (RDD) stands out as a robust strategy for causal inference, relying on weak and easily implemented nonparametric identifying assumptions. These assumptions facilitate flexible and robust identification and inference of local treatment effects. A core feature of RDD is the presence of a score, or running variable, for each unit in the sample. This variable determines treatment assignment through a hard threshold: units with scores exceeding a pre-defined cutoff are treated, while those below are not. Identification, estimation, and inference are achieved by comparing outcomes of units near the cutoff, using those below the threshold as counterfactuals for those above. For recent, comprehensive literature reviews, see Calonico et al. (2017) and Cattaneo and Titiunik (2022).

In this paper, we adopt the potential outcome (or continuity) approach[1], introduced by Hahn et al. (2001). Potential outcomes are taken as random variables, with the n units of analysis forming a random sample from an underlying population, while the running variable, X, is assumed to be continuously distributed. Let $Y_i(0)$ and $Y_i(1)$ denote the potential outcomes for unit i under control and treatment, respectively, and let $T_i \in \{0, 1\}$ indicate the treatment status. The realized outcome is $Y_i = Y_i(T_i)$. Treatment assignment is a function of the pretreatment running variable, X_i, specifically, $T_i = I(X_i \geq c)$, where c denotes the exogenous threshold or cutoff.

Formally, the treatment effect is defined as:

$$\tau = E\left(Y_i(1) - Y_i(0)|X = c\right). \tag{1}$$

Two key assumptions underpin identification. First, the regression functions $E(Y_i(0)|X_i = x)$ and $E(Y_i(1)|X_i = x)$ are continuous in x at c. Second, the density of the running variable is positive near the cutoff. These assumptions embody the idea that units marginally above and below c would exhibit similar average responses if the treatment status did not change. Consequently, any difference in average responses at the cutoff can be attributed to the treatment, representing the causal average effect. This effect is estimated as the discontinuity in the conditional expectation of Y_i as a function of X at the cutoff:

$$\tau = \lim_{X \to c^-} E\left(Y_i|X_i\right) - \lim_{X \to c^+} E\left(Y_i|X_i\right). \tag{2}$$

In practice, we have:

$$\begin{array}{c|c} -h \leq X_i < c & c \leq X_i < h \\ Y_i = \beta_{0-} + (X_i - c)\beta_{1-} + \epsilon_{i-} & Y_i = \beta_{0+} + (X_i - c)\beta_{1+} + \epsilon_{i+} \end{array}$$

where $\hat{\tau}_{RD} = \hat{\beta}_{0+} - \hat{\beta}_{0-}$ is the estimated discontinuity, h is a bandwidth ensuring proximity to the cutoff, and ϵ_{i-} and ϵ_{i+} are error terms.

The core idea is to estimate local regression functions for the control and treatment groups. This, in its basic form, can be accomplished by estimating:

$$Y_i = \alpha + \tau_{RD} T_i + (X_i - c)\beta_1 + \epsilon_i, \quad -h \leq X_i \leq h \tag{3}$$

[1] As a complement to the potential outcome approach, Cattaneo et al. (2015) introduced the local randomization framework, which posits that near the cutoff, the RD design can be interpreted as a randomized experiment, or more precisely, as a natural experiment.

where $\hat{\tau}_{RD}$ is the desired estimated discontinuity and ϵ_i is an error term. As mentioned above, regression is performed on a subsample optimally close to the cutoff to ensure comparability, thus mitigating confounding factors. However, this reduction in observations can lead to less precise estimates and limit the ability to evaluate policies. Thus, it is crucial to identify an optimal bandwidth around the cutoff that optimally balances variance and bias (Imbens and Kalyanaraman, 2012; Calonico et al., 2020).

Typically, researchers use local polynomial methods to flexibly approximate the conditional mean function of the outcome variable given the running variable, above and below the cutoff. A common approach involves using a local linear polynomial and weighted linear least squares, giving higher weights to observations closer to the cutoff. If a discontinuity exists, it is interpreted as the average treatment effect at the cutoff, dependent on assumptions and the specific setting. Both the choice of optimal bandwidth and polynomial degree are critical. Recently, Long and Rooklyn (2020) proposed a machine learning-based method called NEXT. This algorithm simultaneously selects the polynomial specification and bandwidth combination by minimizing the predicted mean squared error at the cutoff. NEXT identifies the optimal combination by evaluating various possible combinations and finding the one that best estimates the next point on both sides of the discontinuity. The performance of NEXT has shown to be satisfactory when compared to commonly used methods, such as those proposed in Imbens and Kalyanaraman (2012) and Calonico et al. (2014).

Given the nature of RDD and its underlying assumptions, a primary analysis is often complemented by a set of supplementary analyses aimed at evaluating its credibility (Cattaneo and Titiunik, 2022). One such analysis is the manipulation test (McCrary, 2008), which assesses the continuity of the running variable at the cutoff. If systematic manipulation of the unit's index occurs around the cutoff, indicating self-selection or nonrandom sorting of units into treatment and control groups, the density of units would be discontinuous, thus invalidating the RDD design. Accepting the null hypothesis of continuity supports the absence of manipulation. Another is to examine whether the RDD yields similar distributions of observed predetermined covariates for the treatment and control groups. Typically, one tests the null hypothesis that the mean of predetermined covariates is the same for treated and control groups. Rejecting this hypothesis indicates non-comparability in terms of predetermined characteristics, raising doubts about the research design. A further analysis is the placebo analysis, where the primary analysis is replicated using a pseudo-outcome, that is *a priori* known to be unaffected by the treatment.

3. Model and data

To evaluate the impact of policy actions and institutional changes in local governance structures on air pollutant reductions in US urban areas, we will leverage the TMA designation as a quasi-experimental framework.

Specifically, focusing on TMA designations following the 2010 Census, we consider as treated units 26 Urbanized Areas (UAs) that, having exceeded the population cutoff $c = 200,000$ in 2010, were hence designated as TMAs for the first time in 2012. Conversely, untreated units are 305 UAs with a population below this cutoff.

The RDD model we estimate is:

$$Y_i = \alpha + T_i \tau_{RD} + (X_i - c)\beta + \epsilon_i, \quad -h \leq X_i \leq h \tag{4}$$

where, for each statistical unit i, Y_i represents the level of traffic-related CO2 emissions in 2015, X_i is the population (running variable), and ϵ_i is the error term. This regression is conducted using UAs with a running variable value close to the cutoff $c = 200,000$, as defined by a bandwidth h.

To perform this analysis, we utilize the following data sources:

- Population and TMA designation: the sources are US Census Bureau and US Federal Register; these sources also provide the shapefiles for the administrative boundaries of the urbanized areas

- Traffic-related CO2: the source is NASA, the data set is DARTE (Database of Road Transportation Emissions) and it provides a 38-year, 1-km resolution inventory of annual on-road CO2 emissions for the conterminous United States based on roadway-level vehicle traffic data and state-specific emissions factors for multiple vehicle types on urban and rural roads.

- Nightlights (used in the supplementary analyses): the source is the Google Earth Catalog, VIIRS Nighttime Day/Night Band Composites Version 1. It provides monthly average radiance composite images using nighttime data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB).

4.Results and discussion

The RDD presented in Section is estimated using a local polynomial approach with optimal selection of polynomial specification (up to order 3), bandwidth (allowing for asymmetry on either side of the cutoff), and kernel (Uniform, Triangular, or Epanechnikov). These parameters are determined via machine learning using the NEXT algorithm by (Long and Rooklyn, 2020). The analysis was performed using Stata 18 and the NEXT package.

Table I displays the optimal specification identified by the algorithm. As shown, the algorithm selects a local polynomial of degree 1 on both sides of the cutoff, using a Triangular kernel on the left side and a Uniform kernel on the right side.

Table I: Best identified specification

	Degree	Kernel	Bandwidth
left-hand side	1	triangular	0.5755
right-hand side	1	uniform	0.6096

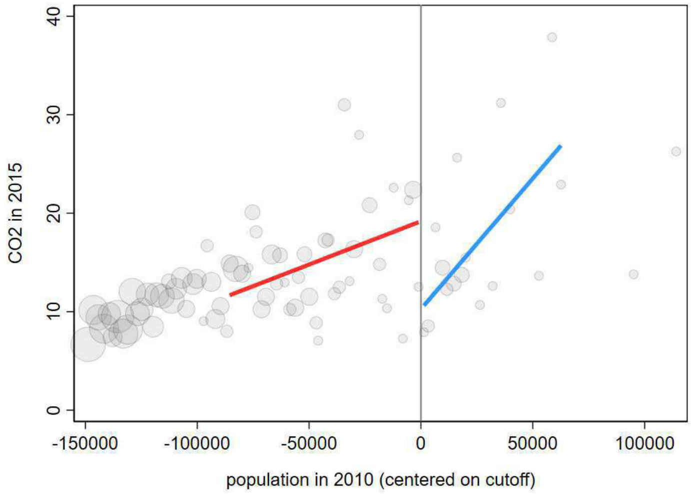
Table II and Figure 1 present the results of the corresponding local estimation. As shown in Table II, the estimated treatment effect is statistically significant and negative, as expected.[2] This finding supports the hypothesis that TMA designation in 2012 has a discernible effect on 2015 traffic-related CO2 emissions. The RD plot in Figure 1 clearly illustrates the discontinuity at the cutoff in the conditional expectation of Y as a function of the running variable; the vertical distance between the two estimated expectations represents the local treatment effect.

[2]The NEXT package employs robust or sandwich estimator of variance.

Table II: Estimation results

	Coeff	Robust SE	t	$P > \|t\|$
Left-to-Right discontinuity	-8.908944	2.613339	3.41	0.0009

Figure 1: Random discontinuity plot for basic RDD with local polynomial regression



Note: data were placed into 120 bins for the purpose of specification search; the size of each circle is proportional to the number of observations it represents.

The results of the supplementary analyses are presented in Table III. We begin with the manipulation test to verify the continuity of the running variable at the cutoff[3]. The first panel of Table III shows that the null hypothesis of continuity is accepted. We then estimate model (4) using CO2 emissions in 1992 as a pre-treatment outcome. This is done to rule out the possibility of a significant discontinuity in the pre-treatment period, as this would undermine the results presented in Table II. The second panel of Table III shows that there is no statistically significant discontinuity at the cutoff in the pre-treatment period. This confirms that a significant discontinuity is only evident after the treatment. Next, we perform a placebo analysis. As a placebo variable for CO2 emissions, we use nightlights, as this variable has been shown in the literature to be a proxy for economic activity (e.g., Henderson et al. (2012)). The rationale behind this choice is the assumption that economic activity should not be reduced by emission containment policies[4]. Nightlights, proxying economic activity and therefore acting as a placebo variable, is expected to remain unaffected by the policy implementation. We first run the regression model (4) using nightlights in 2015 as the outcome variable. The results in the third panel of Table III show no significant discontinuity. This finding reinforces the validity of the significant discontinuity observed in Table II. As a final robustness check, we examine the nightlights placebo outcome in a pre-intervention period by considering the 1992 nightlights. Again, we find no significant discontinuity. Overall, the supplementary analyses confirm the robustness of the results from the primary analysis.

It must be acknowledged that an RDD design with an imbalance in group sizes as in

[3]The NEXT package does not include a manipulation test; therefore, we used the `rddensity` package (Cattaneo et al., 2018), allowing the software to choose an asymmetric bandwidth consistent with the choices made using the NEXT algorithm.

[4]See Li et al. (2020) for details on the harmonization of the nightlights dataset.

Table III: Robust local polynomial estimation: supplementary analyses

Manipulation test

Method	T	$P > \|T\|$
Robust	0.2266	0.8207

Pre-treatment: CO2 1992

	Coeff	Robust SE	t	$P > \|t\|$
Left-to-Right discontinuity	.0171503	4.961272	0.00	0.9973

Placebo outcomes: Nightlights 2015

	Coeff	Robust SE	t	$P > \|t\|$
Left-to-Right discontinuity	-3.460195	2.918355	1.19	0.2387

Placebo outcome (pre-treatment): Nightlights 1992

	Coeff	Robust SE	t	$P > \|t\|$
Left-to-Right discontinuity	-.3611666	3.211726	0.11	0.9107

the present study might raise concerns about the statistical power of the results. However, firstly, we find (Table II) sound statistical significance of the discontinuity shown in Figure 1. Furthermore, the supplementary analyses (Table III) lead us to exclude violations of the RDD underlying assumptions, mentioned in Section . All in all, despite this limitation of the data, we consider the results to be strong enough to suggest that TMA designation may create a framework that encourages the implementation of air pollution containment policies. In particular, our findings based on the TMAs designated in 2012 indicate that these areas achieved a reduction in 2015 CO2 emissions compared to similar urbanized areas that did not establish a TMA.

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