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Measuring the air pollution benefits of public transport projects☆

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ABSTRACT

We discuss two approaches to estimating the air quality impacts of public transit projects, focusing on Metro projects in the context of developing countries: air quality modeling and reduced-form econometric methods. As we illustrate, pollution reductions due to Metro projects implied by pollutant chemistry, vehicle emissions factors, and modal shifts may differ from econometric estimates of the impact of transit projects on ambient pollution concentrations. We discuss both approaches and illustrate how economics researchers can use estimated emissions reductions associated with a transit project and pollutant chemistry as a check on their estimates of changes in ambient concentrations.

1. Introduction

Throughout the world, road transport is an important source of local and global air pollution. Vehicle exhaust produces carbon monoxide (CO), volatile organic compounds (VOCs), oxides of nitrogen (NO_x), sulfur dioxide (SO_2) and particulate matter (PM). These pollutants have health effects in their primary form (i.e., when emitted directly) and when they combine to form secondary pollutants—both particulate matter (e.g., ammonium nitrate and ammonium sulfate) and ozone (WHO, 2013; HEI, 2010). In 2018, the transport sector accounted for 25% of global CO_2 emissions from fuel combustion (IEA, 2019). A substantial portion of the CO_2 transport emissions is attributable to road transportation: 72% for the EU, 81% for the US and 90% for India.[1]

When public transport projects are planned, reductions in air pollution are often cited as benefits of the project, in addition to time savings and reduced congestion. The magnitude of pollution reduction depends on the size of modal shifts from private to public transport, the difference in emissions per passenger kilometer traveled between private and public transport and the number of kilometers traveled. This determines the reduction in emissions due to a project. In the case of CO_2, the reduction in emissions is what matters: the impact on climate of CO_2 is independent of where it is emitted. In the case of local air pollution, the impact of a change in emissions on ambient air quality depends on where the change occurs, and it is the change in ambient air quality that affects human health and welfare.

In this paper we focus on the impact of public transit projects on ambient air quality. The rapidly expanding economics literature on this topic uses reduced-form econometric methods to estimate the impact of projects on ambient CO, NO_x, PM and ozone. One group of studies examines how air quality changes when a public transit strike occurs. Other studies look at how air quality changes after a Metro system is introduced or expanded. These studies are often executed using a regression discontinuity (RD) in time or a difference-in-differences approach. Both sets of studies are capable of providing causal estimates of the impact of public transit on ambient air quality; however, they are ex post studies and measure impacts of inherently different policies. Reduced-form studies face the challenge of controlling for other factors that may affect ambient air quality, such as emissions from other sources and changes in meteorology that also vary over time.

Another approach to estimating the impact of transit projects on ambient air quality is to calculate emission changes at a fine geographic scale and use atmospheric chemistry to calculate their impacts on ambient air quality. Translating emissions reductions into impacts on ambient air quality requires dispersion models that track the transport of pollutants through the atmosphere using information on weather,

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[1] In the EU in 2019, 28.5% of CO_2 emissions came from transport and 20% of CO_2 emissions came from road transport (European Parliament, 2022). In the US in 2021, 29% of greenhouse gas (GHG) emissions came from transport; 81% of transport emissions came from road transport (EPA, 2023). In India in 2020, transportation was the third largest emitter of GHGs; 90% of transport emissions were from road transport (Singh et al., 2022).

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topography, and pollutant chemistry.[2] The advantage of these models, which have been used to model the impact of road transport emissions on fine particle formation, is that they can hold constant factors that are difficult to control in reduced-form econometric models, such as weather and pollution emissions from other sources. They can also be used to estimate the air pollution impacts of a transit projects ex ante. Atmospheric chemistry models are validated by comparing model predictions to measurements of air quality at ground-level monitors.

In this paper we discuss the strengths, limitations and complementarities of two approaches used to measure the local air pollution benefits of public transit: reduced-form econometric models and air-quality modeling. We begin in Section 2 by discussing the atmospheric chemistry of ambient air quality associated with local air pollutants: CO, NO_x, PM and ozone. This has important implications for the selection of data and monitoring sites in econometric studies, and the geographic scale at which air quality modeling is conducted. Atmospheric chemistry can also be used to provide an order of magnitude estimate of the reduction in air pollution from a transit project by examining the percentage reduction in emissions it delivers in a particular location. This can provide a check on the plausibility of econometric results and is particularly relevant given the sensitivity of econometric estimates to model specification.

In Section 3 we review the results of econometric studies of the air quality benefits of transport projects, discussing the methods used and the sensitivity of results to modeling assumptions. We concentrate on the literature in developing countries, focusing on China, India and Taiwan, and studies that examine the air quality benefits of Metro rail. We illustrate the emissions inventory/air quality modeling approach in Section 4, using the Delhi Metro as an example. Section 5 concludes.

2. How public transit can reduce emissions

If a public transit project produces fewer emissions per passenger kilometer traveled than existing transport modes, modal shifts can reduce pollution emissions.[3] In the case of Metro rail, the emissions reductions generated when Metro riders shift from private vehicles to Metro usually occur along roads that parallel the Metro lines, for example, in the downtown or central business district of a city. It is there that empirical studies should focus to estimate reductions in ambient air pollution caused by the transit project. The electricity used to run the trains and provide auxiliary power is usually generated in other areas, where fewer people are exposed to emissions. In most studies, the impact of these emissions is not measured.

What pollutants are reduced when passengers shift to Metro? Primary pollutants emitted by petrol and diesel powered vehicles are CO, VOCs, NO_x, PM and SO_2. Secondary pollutants include ammonium nitrate and ammonium sulfate, which form when NO_x and SO_2 combine with ammonia, respectively, and ozone, which is formed when NO_x and VOCs combine in the presence of sunlight.

The impacts of emissions reductions on ambient air quality depend on where emissions reductions occur. Since most emissions reductions associated with a Metro will occur along roads that are alternatives to riding the Metro, peak reductions in ambient concentrations of primary pollutants will occur along these roads. To understand the magnitude of air quality improvements across space, it is important to understand how fast ambient pollution concentrations from road transport decline with distance from a road. Research has shown that ambient concentrations of nonreactive pollutants (e.g., directly emitted PM and CO) decay rapidly 100–400 m from a major road: concentrations fall to < 20% of peak concentrations in this range (Zhou and Levy, 2007). NO converts rapidly to NO_2, which declines to < 20% of peak concentrations within 200–500 m from the emissions source. So, the biggest reductions in ambient pollution from CO, NO_2 and directly emitted PM are likely to occur close to roads. This implies that, depending on their location, ground-level monitors may not capture all of the reductions in ambient air pollution due to a transport project.[4]

As noted above, road transport also creates secondary pollutants. Fine particles ($PM_{2.5}$) and ozone are especially important because of their impacts on human health (WHO, 2013; HEI, 2010). Fine particles ($PM_{2.5}$) and ozone travel much longer distances, hence focusing on monitors near traffic intersections may not capture all of the impact of a transport project on secondary PM and ozone. These effects can be captured through air quality modeling.

What magnitude of reductions in ambient air pollution is a transport project likely to cause? For primary pollutants, a rough rule is that the percentage reduction in emissions in a given area results in an equivalent percentage reduction in ambient concentrations (Small and Kazimi, 1995; Nagpure and Gurjar, 2012). To estimate the air quality reductions from transport projects, econometric studies often measure the change in primary pollutant concentrations (e.g., CO, NO_2 and PM_{10}) at ground level monitors. Note that ambient concentrations of primary pollutants at a monitor will reflect mainly emissions within a radius of approx. 2–4 km of the monitor, based on the decay rates cited above. If passenger transport constitutes 40% of CO emissions within this area, and if 10% of CO emissions from passenger transport in the area are reduced by a Metro project, ambient CO should fall by 4%. The important question for evaluating the air quality impact of a Metro project is what percent of pollutant emissions in a given location come from passenger transport and what percent of these emissions is reduced by modal shifts. This can be used as a reality check on the magnitude of results found in econometric studies.

3. Econometric studies estimating the impact of transport projects on air pollution

There have been many studies in the economics literature attempting to estimate the air pollution consequences of transport policies, including expansions of Bus Rapid Transit (BRT), Metro rail, light rail and intercity rail projects, strikes affecting transportation services, and various driving restrictions. While these are all based on similar approaches and have the common aim of understanding the environmental impacts of public transit, we focus on studies conducted to measure the air quality effects of Metro rail projects. We also focus on developing countries since many developing countries have Metro projects underway. These studies are summarized in Table 1. Other studies analyzing the importance of public transit are in Appendix Table A.1.

Empirical papers studying the influence of Metro transit projects on air quality often rely on event study approaches, such as regression discontinuity (RD) in time or difference-in-differences (DiD). The RD in time approach allows researchers to estimate the change in the level of a pollutant potentially caused by the introduction of a project. The implicit assumption is that in the absence of the project, pollution levels would have changed smoothly, without any discontinuous jumps.

This approach has been used to study the air quality impacts of Metro systems by Chen and Whalley (2012) in Taipei, by Goel and

[2] Dispersion models may be either process-based or reduced form (NRC, 2010). Process-based models (e.g., CAMx, CMAQ) use detailed atmospheric chemistry to simulate interactions among pollutants and gases in the atmosphere and thus account for nonlinearity in the dispersion process. Reduced-form models (e.g., ATMoS, CALPUFF, HYSPLIT) use simplified dispersion calculations to predict concentration changes.

[3] This is definitely true if kilometers traveled remain constant, but may not hold if there is a rebound effect—i.e. if passengers travel farther on public transit.

[4] Reductions in road transport emissions will, nevertheless, have significant human health benefits given the number of people directly exposed to them (see Brunekreef et al., 2009; HEI, 2010; WHO, 2013).

Table 1
Published studies examining the effects of subways or commuter rail on air pollution using econometric methods (Economics or Transportation Journals).

Study	Context	Empirical approach	Pollutants examined	Results
Chen and Whalley (2012)	Introduction of the first Metro line in Taipei in 1996	Main: RD in time for 1 year before and after the policy; Robustness: DiD comparing two cities	CO, O_3, NO_x, PM_{10}, SO_2	5%–15% reduction in CO, a statistically insignificant reduction of 8% in NO_x, an unclear effect on O_3, no effects on PM_{10} and SO_2
Goel and Gupta (2017)	Two early extensions to the Delhi Metro in 2005 and 2006	RD in time for about 18 months before and after the policy	NO_2, CO, and $PM_{2.5}$	34% decline in CO measured at the ITO monitoring station; weak or no effects on other pollutants
Gendron-Carrier et al. (2022)	Subway openings in 58 cities from 2001–16, mostly in developing countries	RD in time, 18 month before and 18 months after	AOD data measured monthly at 3 × 3 km resolution	No average effects of subway openings within a radius of 10 km around the city center, but a 4% average reduction in cities with above-median baseline levels of AOD
Li et al. (2019)	Beijing Metro expansion	Main: Historical routes as an instrumental variable for subway density; Robustness: spatial DiD comparing monitors within 2 km of a subway station with locations farther than 20 km away	Daily AQI based on SO_2, NO_2, PM_{10} for a part of the period and one based on CO, SO_2, NO_2, PM_{10}, $PM_{2.5}$, O_3 for the remainder	Reduction in pollution ranging from 0.02% from the opening of Line 16 (20 km length) to 0.24% from the opening of Line 6 (78 km length); aggregate decline of 1%; 7.7% decline in pollution from DiD
Guo and Chen (2019)	Beijing Metro expansion	RD in time, 50–80 days before and after the policy	$PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, O_3, AQI	Reductions in $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, AQI by more than 155%, 125%, 78%, 110%, 109%, 112%, respectively. Over 100% increase in O_3.
Zheng et al. (2019)	Changsha Metro	DiD, one year before and 1 year after	Hourly CO, O_3 and $PM_{2.5}$	18% reduction in CO, no effects on O_3 and $PM_{2.5}$
Guo et al. (2020)	23 Inter-city high-speed railway lines in China opened during 2015–16	DiD comparing stations within 10 km of highways affected by new HSR lines v. those within 10 km of old HSR lines	CO, O_3, $PM_{2.5}$	4.3% reduction in CO. No effect on other pollutants
Lee et al. (2023)	Opening of a high-speed rail line connecting two megacities in China in 2015: Chengdu and Chongqing	Main: Two-step approach with random forest in the first stage and an augmented RD in time approach in the second stage; Robustness: DID comparing affected roads with randomly chosen roads	Hourly $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO and O_3 from an AQM at 15 km resolution	6.4% reduction in CO along the main affected highway, 7.1% decrease in $PM_{2.5}$, 2.2% decrease in PM_{10} levels. No effect on NO_2 and O_3. DiD estimates are larger and NO_2 declines significant, O_3 shows significant increase.

Note: Main empirical approach is described unless otherwise noted.

Gupta (2017) in Delhi, by Guo and Chen (2019) in Beijing, by Gendron-Carrier et al. (2022) in 58 cities, and by Cropper and Suri (2022) in Mumbai. Some papers also feature a DiD approach, which estimates the change in the level of a pollutant due to the transit project in a location that received the transit project relative to a location that did not: for example, Chen and Whalley (2012) in Taipei, Li et al. (2019) in the context of the Beijing Metro expansion, and, Zheng et al. (2019) in Changsha. This method assumes parallel trends in pollution levels in the treatment and control locations in the absence of the project.

These approaches have also been used to study the air quality impacts of other public transit projects in developing countries, such as the expansion of BRT in Mexico city (Bel and Holst, 2018), the re-organization of bus routing and scheduling in Santiago, Chile (Gallego et al., 2013), and the introduction of high-speed inter-city rail in China (Guo et al., 2020; Lee et al., 2023).[5] In this paper, we focus only on the measurement of air quality impacts of Metro projects.

3.1. Pollution measurement units and locations

In all of the studies in Tables 1 and A.1, the goal is to estimate the effect of a policy on ambient air quality measured by ground level monitors or aerosol optical depth (AOD).[6] Researchers have studied the effects of Metro rail on both primary (CO, NO_x, PM_{10}) and secondary pollutants ($PM_{2.5}$), for time spans ranging from 30 days to 2 years before and after the policy. In terms of primary pollutants, studies estimating the impacts on CO have found wide-ranging reductions: 5%–15% in Chen and Whalley (2012), 34% in Goel and Gupta (2017), 78% in Guo and Chen (2019), and 18% in Zheng et al. (2019). Evidence about the effects on NO_x or NO_2 is weaker: Chen and Whalley (2012) and Goel and Gupta (2017) find reductions in NO_x and NO_2 that are not stable across specifications.[7] Chen and Whalley (2012) and Cropper and Suri (2022) also do not find significant reductions in PM_{10}. Of studies that evaluate $PM_{2.5}$, Goel and Gupta (2017), and Zheng et al. (2019) do not find significant reductions. Guo and Chen (2019) document reductions in PM_{10} and $PM_{2.5}$, but their estimated reductions exceed 100%, and are likely confounded by other factors. Gendron-Carrier et al. (2022) find no average effects across 58 cities on AOD, a proxy for PM, however, there is a reduction in cities with above-median baseline levels of AOD and substantial ridership.

Changes in air quality are expected to arise due to modal substitutions, which, for primary pollutants, will occur on roads close to the Metro network. Many researchers, therefore, restrict their treatment

[5] For studies examining other transportation policies in both developing and developed countries, see Li et al. (2020).

[6] AOD is a measure of aerosols present in the atmosphere based on the extinction rate of a ray of light passing through the atmosphere. It is often used to proxy surface-level PM, but the relationship varies based on meteorological conditions and atmospheric chemistry.

[7] Guo and Chen (2019) find reductions in NO_2 ranging from 78% to over 100%. Cropper and Suri (2022) find reductions in NO_2, that represent the effect of the opening of Metro Line 1 and a highway expansion project that opened during the same month.

locations to areas in the vicinity of Metro projects, where traffic is most likely to be affected (Goel and Gupta, 2017; Gendron-Carrier et al., 2022; Li et al., 2019).[8] But sometimes, for practical reasons, researchers analyze ambient air pollution reductions averaged over a very large area.

While it is true that pollutants travel and are persistent, it would be naïve to claim that econometric studies estimate the pollution reduction due to the policy, without accounting for the chemistry of dispersion and persistence of a pollutant between the location of emission and the location of measurement. Gendron-Carrier et al. (2022), for example, document a spatial decay in the effect of Metro openings on AOD as the treatment area is expanded beyond the city center.

Additionally, when hourly pollution data is used, the level of data aggregation and analysis can also affect the results. For example, should data be aggregated at the hourly level or daily level using measurements from rush hour times? Which are the relevant summary statistics to be examined: mean, median, maximum, or standard deviation? Generally, pollutants emitted by light passenger vehicles peak during rush hour and stabilize during nighttime. Similarly, levels of pollutants emitted by heavy freight vehicles would be higher during the hours they are allowed to operate. Appropriate measurement duration would depend upon the policy in question and the temporal persistence of the pollutants. Fig. 1 for Delhi, for example, emphasizes diurnal patterns for three pollutants: $PM_{2.5}$, CO, and NO_x. $PM_{2.5}$ peaks at night and stays high during the morning rush hours. NO_x and CO peak at night and are lower during the day. This is likely due to heavy vehicles that are allowed to operate only at night.

Some of the variation in econometric estimates across contexts is expected due to differences in the importance of passenger vehicles in the emissions inventories of various pollutants. But, sometimes, the effect sizes estimated within a study are wide ranging, calling into question the reliability of the estimates. Most researchers attempt to use contextual knowledge to explain the sensitivity of estimates, but this varies across contexts and journals. In the following subsection, we describe the reduced form approaches commonly used for estimating the impact of a Metro project on air pollution, highlighting the implications of specification choices that may lead to unstable estimates of impacts on air pollution.

3.2. Methodological approaches

Regression Discontinuity: Given data on ambient pollutant concentrations before and after the opening of a project, most papers using an RD in time regress the log of a pollutant concentration, measured hourly or daily at a ground-level monitor, on an indicator variable for the period after the project opening, a flexible polynomial time trend, controls for meteorological conditions, and a combination of fixed effects for hour of the day, day of the week, month, and year. The rationale is to identify the effect of the policy on pollution levels while accounting for trends in observed ambient levels regardless of the emission source, i.e., including non-transport sources, which may vary by time of day, day of the week and season of the year.

To illustrate the need for these controls, Fig. 2 plots the average hourly levels of PM_{10} for a 30-day period before and after the opening of the first Taipei Metro Line using data from Chen and Whalley (2012). PM_{10} levels peak during Wednesday–Friday and are lower during morning hours. Over a longer period, we would also observe a pattern based on climate conditions during different seasons. The pattern in hourly variation is also seen in Fig. 1 for Delhi. Additionally, pollution levels are affected by meteorological conditions such as humidity, temperature, and wind conditions, but given the complexity of this dependence, there is variation in how different studies control for these factors.

[8] Other studies examine the heterogeneity in estimates using information from different monitoring stations (Chen and Whalley, 2012).

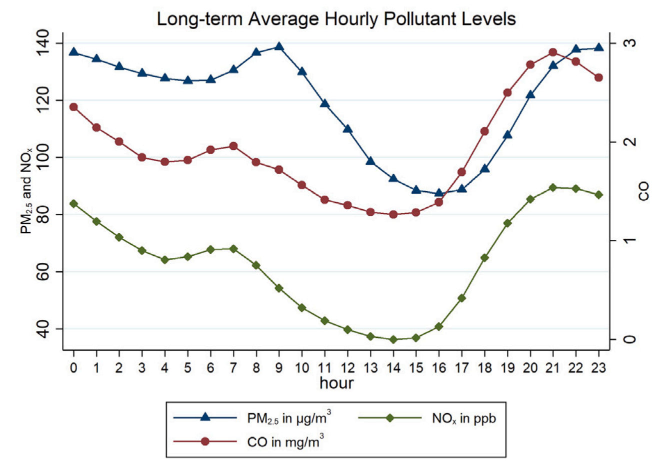

Fig. 1. Delhi pollution averages by hour of the day.
Note: This graph shows the average hourly pollution levels for the period 2013–2023 at the ITO Monitor calculated using data from the Central Pollution Control Board of India.

The estimation equation for the RD in time approach generally takes the following form.

$$\log(\text{Pollutant})_t = \alpha_0 + \delta * \text{Post Policy}_t + \alpha_x * X_t + \beta_k * f(t;k) + \beta_k^{post} * f(t;k) * \text{Post Policy}_t + \epsilon_t \quad (1)$$

For example, in Chen and Whalley (2012), the authors regress the log of the average hourly pollutant level on an indicator variable for the post-Metro period (Post Policy$_t$), a third-order polynomial time trend in days ($f(t;k)$), an interaction of this polynomial trend with the post-Metro indicator allowing the trend to be different in the pre-period and post-period, a vector of covariates (X_t) accounting for meteorological conditions, and fixed effects for month, day of the week, hour, and hour multiplied by day of the week. They also include indicators for other confounding events such as gas content regulations: two before the Metro opening and two after. Meteorological variables include current and 1-hour lags of quartic functions of temperature, wind speed, and humidity. Other papers in the literature follow similar approaches with some variations: for example, in the order of polynomials, choice of controls, and by allowing a differential time trend in the pre and post periods.

Note that this approach is different from a typical RD design, as explained in Hausman and Rapson (2018), but is to a great extent compatible with current RD methods (Lee and Lemieux, 2010; Cattaneo and Titiunik, 2022). Therefore, many of the same issues apply here. Most of the papers using the RD in time approach employ parametric estimation, but given the sensitivity of this approach to polynomial order and controls, it is advisable to employ non-parametric methods as well for robustness.[9] Most notably, including a higher order polynomial time trend can lead to overfitting and inconsistent estimates of the treatment effect (Hausman and Rapson, 2018), but this point has often been ignored in the literature.[10,11]

[9] Calonico et al. (2017) discusses estimation procedures in Stata. See https://rdpackages.github.io/rdrobust/ for details on latest available estimation programs.

[10] Sensitivity to the order of polynomial trend is noted in the Appendix of Chen and Whalley (2012).

[11] Lee et al. (2023) is an exception in that the authors use a local linear regression to estimate the effects of the opening on high-speed rail. However, they follow a different approach by first using the random forest algorithm with the pre-period data to find the best predictors of pollution levels and then obtaining predictions for the entire sample. The prediction errors are the dependent variable in the local linear regression.

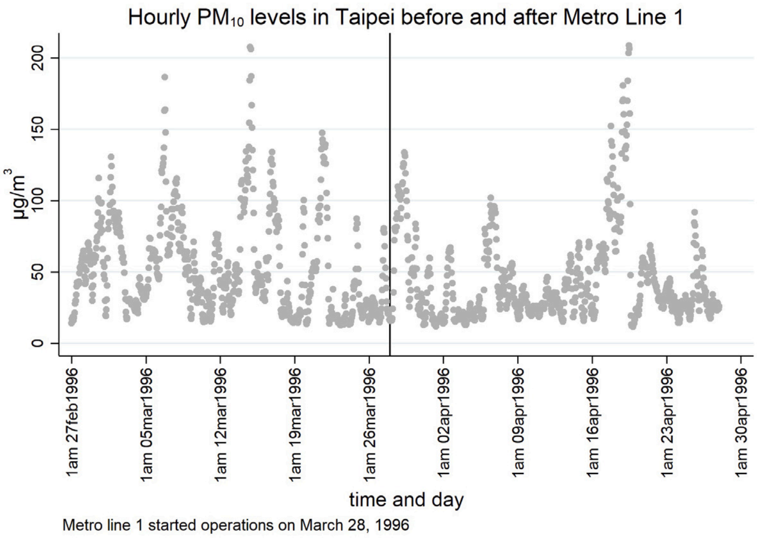

Fig. 2. Trends in Hourly PM_{10}.
Note: This graph shows the emissions of PM_{10} at the hourly level averaged across all monitoring stations used in the analysis of Chen and Whalley (2012) for one month before and after the opening of the first Taipei Metro line. For ease of identifying patterns, x-axis labels are shown for each Tuesday at 1am.

To illustrate the issue of overfitting, we use data on two monitoring stations close to the Taipei Metro Line provided by Chen and Whalley (2012) in their replication files. We show scatterplots using hourly data from 7am to 7pm with fitted polynomial trends of orders 1 through 4 at the hourly level in the left panel of Fig. 3. In a general RD in time specification the polynomial time trend captures secular trends in the level of pollution unexplained by other covariates. If the researcher does not include any covariates, the estimated effect of the policy on pollution is the magnitude of the discontinuity in the polynomial. It is clear from the graphs that fitting polynomials of different orders can have vastly different implications. The magnifications in the plots also make it clear that ex ante there would be no reason to prefer one specification over another.[12]

Estimates from RD in time studies are sometimes sensitive to the choice of sample window around the transit project opening date. Therefore, researchers use multiple samples to test the robustness of their estimates. For example, in Chen and Whalley (2012) the main sample is restricted to one year before and one year after the Metro opening; however, they also use a smaller 30-day window around the opening date to obtain local effects. Goel and Gupta (2017) consider samples of roughly 2.5 weeks, 4.5 weeks, and 18 months before and after the opening date, while Gendron-Carrier et al. (2022)'s main analysis considers a period of 18 months before and after the policy. Fig. 3 shows a comparison of estimates derived using windows of one year v. 30 days before and after the policy without any covariates other than the time trend. The differences in the magnitude of the discontinuity across graphs highlights the influence of polynomial order and sample window on estimates obtained using an RD in time approach.

Smaller windows lead to estimates of the effect closer to the opening and may be less susceptible to the influence of temporal unobserved factors. Therefore, in these analyses, controls for meteorological conditions or polynomial trends are not included. This is similar to a local randomization framework (Cattaneo and Titiunik, 2022): the implicit assumption is that the treatment timing in this short window is random and that potential outcomes are not affected by time.[13] For this approach to be valid, the assumption of random assignment to treatment in time needs to be carefully examined. For example, if a transit project opens at the beginning of the monsoon season or the holiday season, the use of local randomization will likely not be appropriate. Given the sensitivity of the sign and magnitude of RD estimates to bandwidth selections and covariates, researchers must justify these methodological choices and provide results from a variety of sensitivity tests. Additionally, researchers must also use contextual knowledge to check if the estimated policy effect is confounded by the occurrence of another event.

Difference-in-Differences (DiD): Some studies use a DiD approach, comparing changes in the level of a pollutant after the transit project in locations that received the project with the corresponding change in suitable comparison locations. A two-way fixed effects equation with standard errors clustered at the unit level, but preferably at the unit and time levels, is the commonly used estimation approach,[14]

$$\log(\text{Pollutant})_{it} = \alpha_0 + \alpha_1 * \text{Post Policy}_t + \alpha_2 * \text{Treatment Group}_i + \delta * \text{Post Policy}_t * \text{Treatment Group}_i + \gamma_i + \beta_t + \epsilon_{it} \quad (2)$$

where γ_i and β_t represent unit and time fixed effects, respectively and δ represents the main parameter of interest.

Researchers have used different treatment and control groups across projects. For example, as a robustness check, Chen and Whalley (2012) compare Taipei with the city of Kaohsiung in a 30-day window around

[12] With covariates included in the model, the estimated policy effect takes into account the relationship between the covariates and pollution as well as the relationship between time and the covariates (Frisch–Waugh–Lovell theorem). So, in almost every context, the results will likely be different from those implied by the graphs in Fig. 3.

[13] This assumption is stronger than the continuity assumption implicit in the usual polynomial approach since it assumes that inside the window time does not affect potential outcomes.

[14] See Cameron et al. (2011) on a discussion of clustering standard errors at the unit level v. two-way at the unit and time levels.

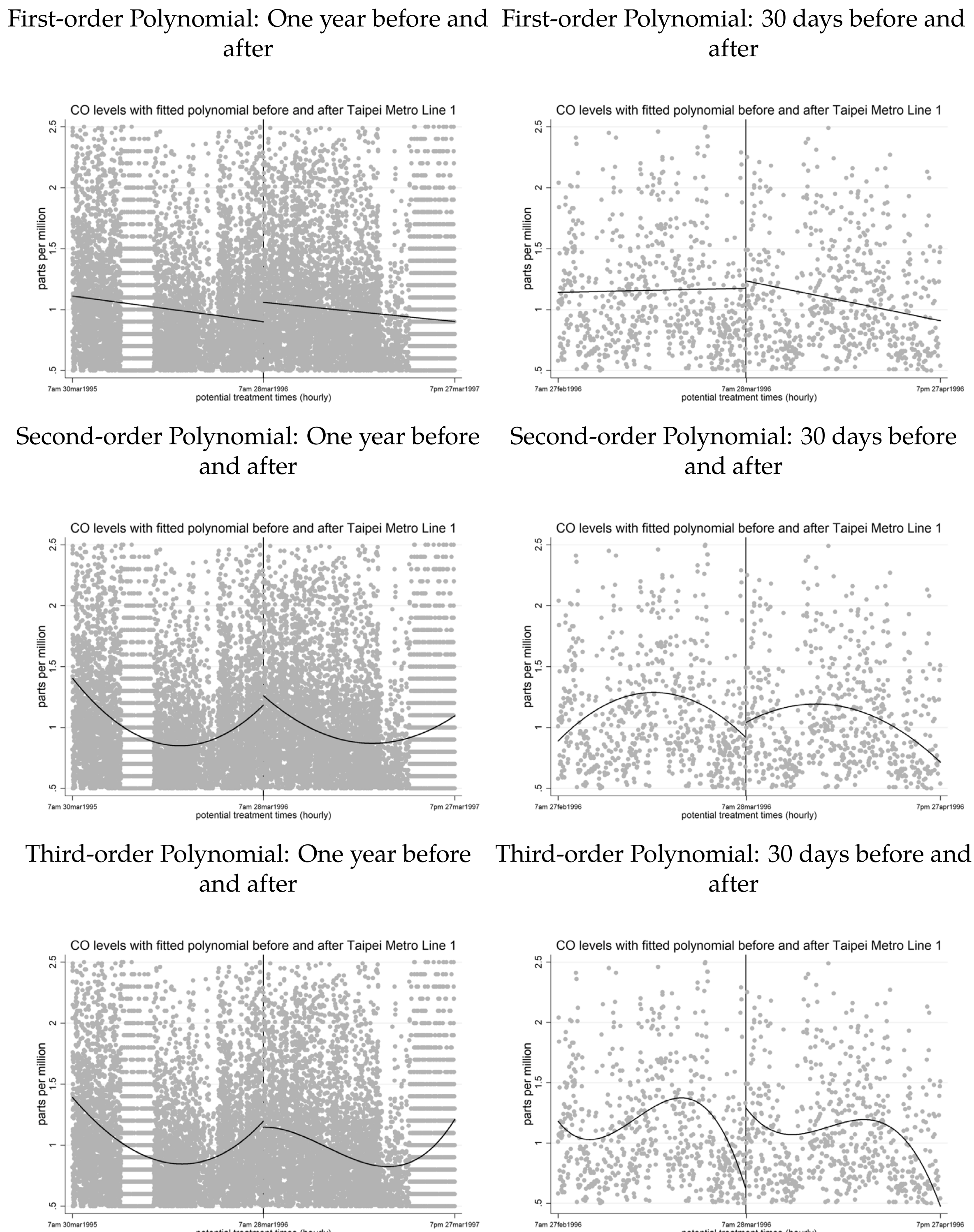

Fig. 3. Scatterplots of CO with varying polynomial trends and sample periods.
Note: These graphs show scatterplots of CO levels at 2 of the 5 monitoring stations that are classified as being near the Taipei Metro line in the dataset of Chen and Whalley (2012) for periods of 1 year (left panel) and 30 days (right panel) before and after the opening. Graph scale is restricted to emphasize the difference in the magnitude of the discontinuity on treatment date. Polynomial trends are fitted on raw data without controls.

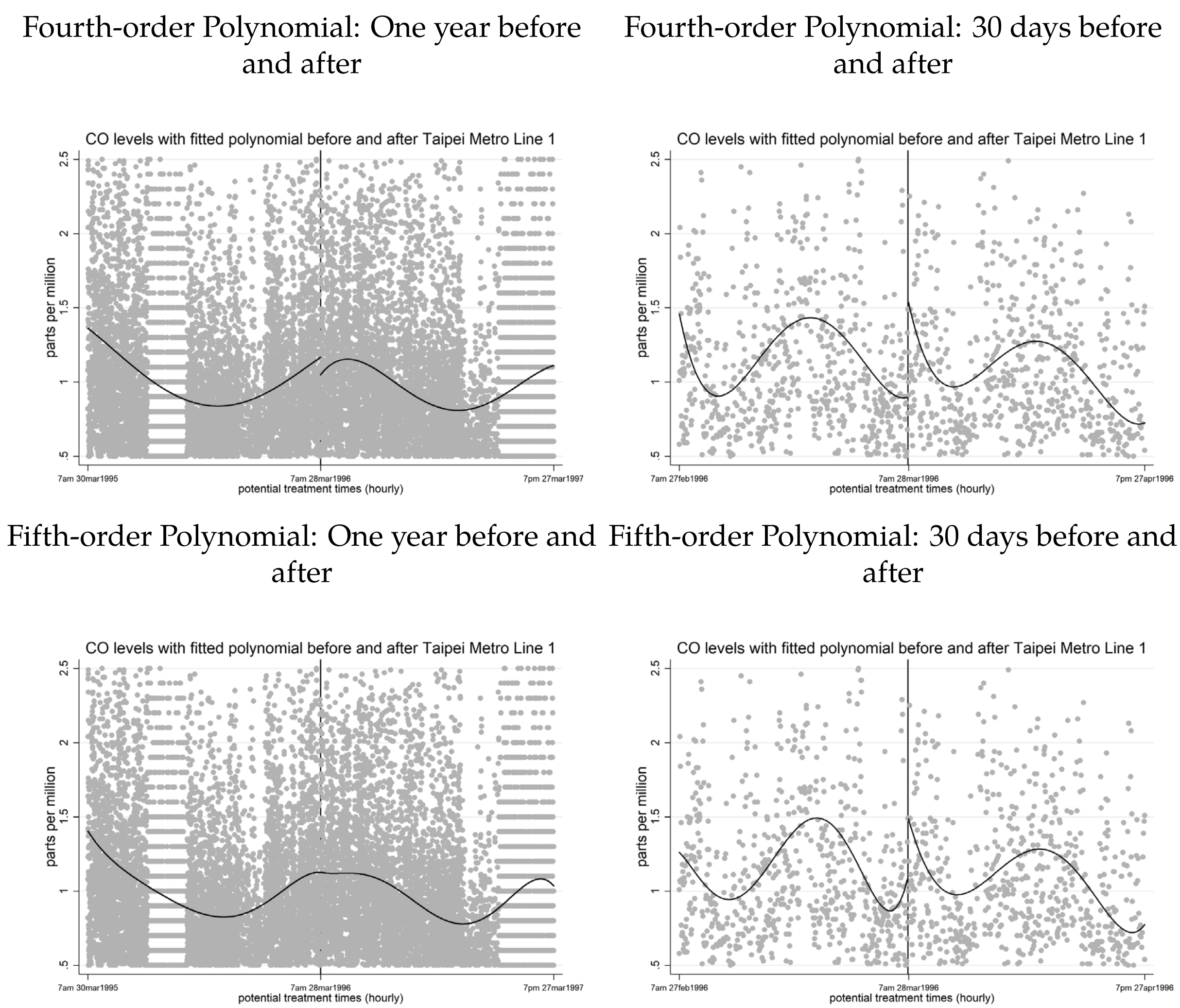

Fig. 3. (*continued*).

the date of Taipei Metro opening. Some researchers use spatial difference-in-differences to compare areas in the vicinity of a transport project to areas beyond the treatment areas before and after project implementation. For example, Li et al. (2019) compare monitors within 2 km of the Metro station with those that are farther than 20 km from it. Lee et al. (2023) also use difference-in-differences in a robustness check, comparing pollution levels along road segments affected by high-speed intercity rail and randomly selected segments of unaffected roads in the same geographical area.

The chosen comparison location in the DiD approach is assumed to mimic the pollution change in the treatment location in the absence of the policy (parallel trends assumption). That is, it is assumed that there would have been a constant difference in pollution levels between treatment and control locations in the absence of the transit project. This is an assumption that must be made by the researcher and is inherently untestable. It is problematic because transit projects are strategically placed to maximize use, and the locations that have them are inherently special. Therefore, researchers should carefully use pre-period data to test for possible violations of parallel trends and account for the magnitude of bias that may be present (Rambachan and Roth, 2023; Roth et al., 2023).

In the absence of any appropriate comparison locations, researchers can combine multiple locations to construct a synthetic comparison group. The change in pollution in the treatment location is computed relative to the change in pollution in the synthetic comparison location. One way to execute this is to use the synthetic DiD estimator in Arkhangelsky et al. (2021), which constructs the synthetic control group by weighting observations based on both cross-sectional and temporal similarity criteria.[15] A common issue with the DiD approach is the presence of spillovers from the treatment to the control group, leading to a violation of the Stable Unit Treatment Value Assumption (SUTVA), and incorrect estimates of the transit project impact. Li et al. (2019) deal with this possibility in the context of the Beijing Metro by making sure that the treatment and control location monitors are spatially separated by a buffer of at least 18 km. In the presence of spillovers, the synthetic DiD estimator reduces the severity of bias of the two-way fixed effects estimator used in the literature (Arkhangelsky et al., 2021).[16]

[15] Traditional approaches construct the synthetic control group based mainly on cross-sectional similarity.

[16] This is due to the inclusion of both unit and time weights. More weight is assigned to pre-treatment periods where control group outcomes more closely resemble post-treatment control group outcomes and more weight is assigned

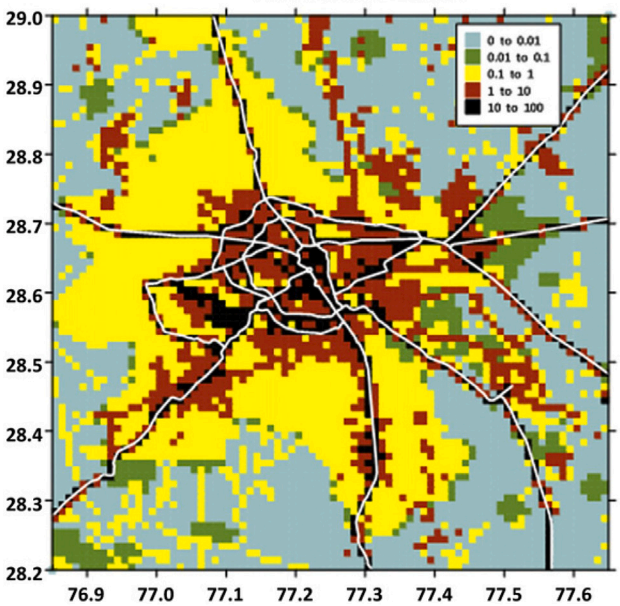

Fig. 4. Vehicle exhaust emissions of PM_{10} in tons/year/grid.
Note: This map shows the emissions of PM_{10} from vehicle exhaust at the 1 km grid level estimated by Guttikunda and Calori (2013).
Source: From Guttikunda and Calori (2013).

Summary: Quasi-experimental econometric methods can be used to estimate the causal impacts of transit projects on air quality, but face several challenges. First, researchers must select measurement locations that are most likely to capture emission changes from the transit policy in question. Second, measurements should be considered for the time period during which modal substitutions due to the transit project are most likely to affect air quality. Third, the influence of the polynomial order, sample period, and control variables on regression discontinuity estimates should be carefully analyzed and reported. Fourth, the selection of treatment and control locations should be carefully justified and sensitivity of results to the exact definitions explored.

Additionally, for the event study approaches outlined above to causally identify the impact of a transit project on pollution, it must be the case that no other policies affecting pollution occur simultaneously with the transit project. This is difficult to verify in practice, but most researchers attempt to use contextual information to investigate this possibility.[17] These challenges underscore why it is advisable, if possible, to compare econometric estimates with the magnitude of emissions reductions one might expect from modal shifts. We do this in the next section in analyzing the air quality impacts of the Delhi Metro.

to control units where the growth in pre-period outcomes is similar to that of treated units.

[17] For example, dummy variables may be included in an RD equation to record the timing of relevant policies. This has been done to capture the introduction of gas content regulations in Taipei (Chen and Whalley, 2012), the opening of different Metro routes in Delhi (Goel and Gupta, 2017), and the imposition of driving restrictions in Beijing (Li et al., 2019). Some studies estimate the impact of such events on pollution as a placebo test, for example, in Cropper and Suri (2022), the opening of the first two phases of Eastern Freeway in Mumbai are placebo events for the opening of Metro Line 1.

4. An emissions/air quality modeling approach to estimating the impacts of a public transit project on air quality: The case of the Delhi Metro

To use an air quality modeling approach to evaluating the impacts of a Metro project requires parameterizing an air quality model at a fine spatial scale (e.g., 1 km × 1 km). This entails obtaining an emissions inventory – based on all sources of the criteria pollutants – at this scale, and appropriate meteorological inputs. After the model is run to obtain ambient concentrations of the pollutants, results (e.g., ambient concentrations of PM_{10}) are compared with monitoring readings to validate the emissions inventory.[18]

Guttikunda and Calori (2013) have developed an emissions inventory for Delhi for 2010 at a 1 km × 1 km scale. Their model covers the National Capital Territory and surrounding areas, a total area of 80 km × 80 km. Table 2 shows their estimates of emissions of $PM_{2.5}$, PM_{10}, SO_2, NO_x, CO and VOCs from the transport sector in 2010 and the percent of emissions of each pollutant contributed by transport. Transport accounts for over half of the emissions of NO_x and VOCs in Delhi, 18% of CO emissions, 13% of PM_{10} emissions and 17% of $PM_{2.5}$. Fig. 4 shows the spatial pattern of PM_{10} emissions from transport: Most emissions are concentrated along major roads. This represents all forms of road transport, including heavy duty and light duty goods vehicles. Indeed, over half of PM_{10} was estimated to come from goods vehicles rather than passenger vehicles (Goel and Guttikunda, 2015). The majority of NO_x emissions were also estimated to come from goods vehicles rather than passenger vehicles, although the reverse was true for CO emissions (Goel and Guttikunda, 2015).

The Delhi Metro first opened in 2002. By November of 2006, Phase I of the Metro, consisting of 59 stations and 65 km of track had been completed (see Fig. 5). By September of 2011, Phase II, consisting of 123 km of track had opened, yielding the network pictured in Fig. 6. The area occupied by the network in 2011 covered 1100 km^2–most of the National Capital Territory of Delhi.

Evaluating the impact of the Delhi Metro using air quality modeling begins with an evaluation of the georeferenced reduction in emissions that is likely to result from the project. Ignoring the local pollutants generated by the electricity which powers the Delhi Metro, the sum of reductions in pollutant i from passengers who shift to the Metro from mode m can be calculated as:

$$\text{Emissions reduced}_i = \sum_m \text{Passengers shifted from mode m} * e_{im} * l_m \tag{3}$$

where e_{im} is grams of pollutant i emitted per passenger km traveled (pkt) on mode m and l_m is average trip length on mode m in km/day.

After a transit project opens, modal shifts can be estimated by surveying users to find out the modes of transport previously used. In the case of the Delhi Metro, Sharma et al. (2014) estimate that in 2011, 55% of the 2 million daily Metro riders had previously used the bus, 20% had traveled by two-wheeler, 20% by car and 5% by three-wheeler. Doll and Balaban (2013) estimate that 44% of Metro riders shifted to Metro from bus, 25% from two-wheelers, 22% from car, 4% from taxis and 5% from three-wheelers.[19]

[18] Note that for this purpose, models are usually run at a fine (e.g., 1 h) time scale. Emissions inventories also vary by hour of the day, day of the week and month of the year.

[19] Together with occupancy rates, these data can be used to calculate the number of vehicles removed from the road for purposes of calculating congestion impacts. If 400,000 passengers on the Delhi Metro would have ridden two-wheelers, and the occupancy factor is 1.5 passengers per two-wheeler, 266,667 two-wheelers have been removed from the road—at least near Metro lines. Sharma et al. (2014) estimated that in 2011, the Delhi Metro removed over 500,000 vehicles from the roads: 27,800 buses, 267,000 two-wheelers, 167,000 cars and 40,000 three-wheelers–approximately 1.5% of the vehicle fleet.

Table 2
Delhi transport emissions inventory in 2010 and estimated reductions due to the Delhi Metro (tons/year).

Pollutant	$PM_{2.5}$	PM_{10}	SO_2	NO_x	CO	Study
Transport Emissions	10,900	14,600	700	198,900	256,200	Guttikunda and Calori (2013)
Percent of Total	17%	13%	2%	53%	18%	
Reduced by 2011 Metro		107		1,320	3,882	Sharma et al. (2014)
Reduced by 2011 Metro		163		1,443	6,545	Doll and Balaban (2013)
Reduced by 2006 Metro		23		299	1,097	Sharma et al. (2014)

Estimates of transport emissions by pollutant are from (Guttikunda and Calori, 2013) and pertain to the NCT and surrounding areas, an area of 80 km × 80 km. The percent of total emissions of each pollutant attributable to transport (row 2) also pertain to this area. Estimates of emissions reduced by the Delhi Metro, as of 2011, are bottom-up estimates, provided by Sharma et al. (2014) and Doll and Balaban (2013). They reflect the authors' estimates of changes in modal shares, average km driven, by mode, emissions factors for different classes of vehicles and vehicle occupancy rates.

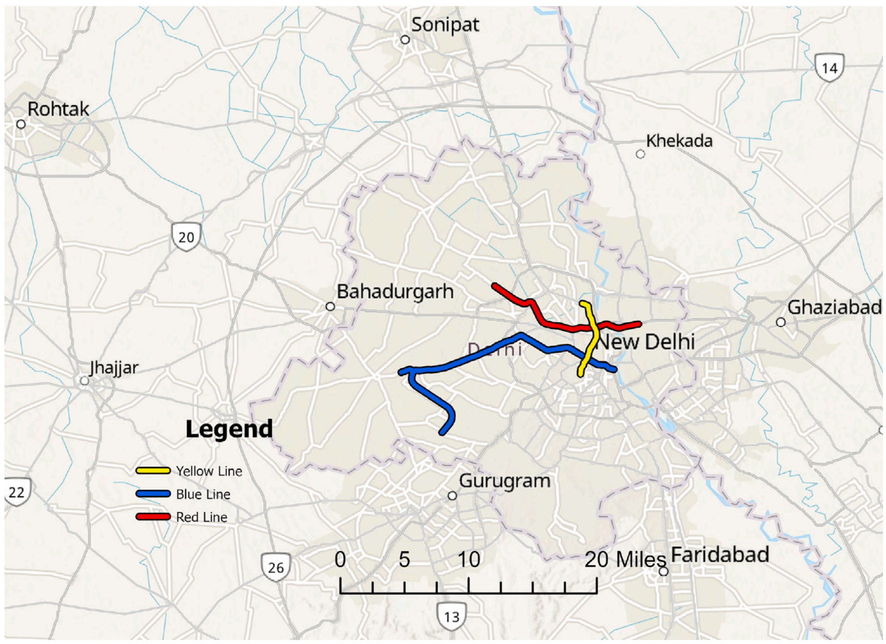

Fig. 5. Delhi Metro 2006.

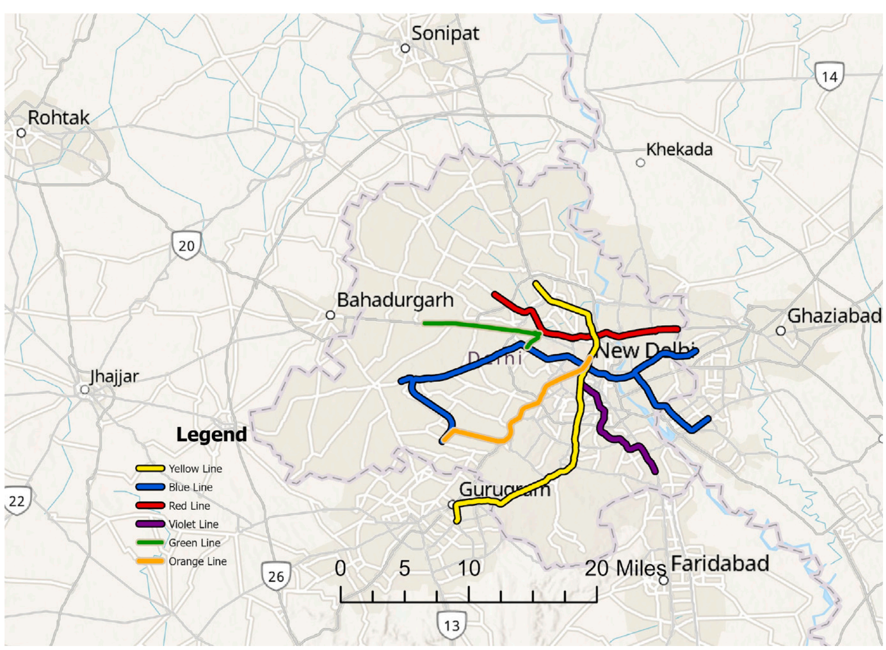

Fig. 6. Delhi Metro 2011.

To calculate emissions per pkt requires estimates of emissions in g/km, for each mode and pollutant, as well as vehicle occupancy rates. Emission factors per km depend on the type of fuel burned (diesel, petrol, CNG), vehicle fuel economy, and use of pollution control equipment. Because these factors vary by vintage of vehicle, calculating emissions reductions requires information, by mode, on the vintage of vehicle fleet. Emissions in g/km may be based on emissions testing information (and adjusted for deterioration factors) or information on emissions in real-world situations (Raparthi et al., 2021). Together with average occupancy factors, g/pkt can be calculated.

Table 2 presents estimates of the annual tons of PM_{10}, NO_x, CO and VOCs emissions reduced by the Delhi Metro in 2011. Estimates by Sharma et al. (2014) are very similar to those of Doll and Balaban (2013) for PM_{10}, NO_x and VOCs, but differ for CO. This is due in part to the higher share of riders estimated by Doll and Balaban (2013) to come from two-and four-wheelers. Estimates of tons of emissions reduced by Phase I of the Metro in 2006 (Sharma et al., 2014), when daily ridership was approximately 451,000 per day, are also in Table 2.

To use atmospheric chemistry to estimate the impact of the reductions in emissions associated with the Metro requires that an atmospheric chemistry model be run with and without the emissions reductions in Table 2, both georeferenced. This has not been done for Delhi; however, the information in Table 2 can be used to place bounds on the magnitude of the air quality improvements associated with the Delhi Metro.

The air quality monitoring station at the Income Tax Office (ITO) in central Delhi has been the focus of air quality analyses for many years (Guttikunda and Calori, 2013; Nagpure and Gurjar, 2012) given its location at a major traffic intersection. The ITO is also located near the intersection of Yellow and Blue lines of the Delhi Metro (see Figs. 5 and 6). As noted in Section 3, Goel and Gupta (2017) have used a regression discontinuity design to examine the impact of the extension of the Yellow line in July of 2005 on air quality at the ITO monitoring station. They find that this extension reduced CO at the ITO by 34% between 2004 and 2006. A 34% reduction in CO concentrations at the ITO would require a 34% reduction in CO emissions near the ITO monitor. Nagpure and Gurjar (2012) estimate only a 4% reduction in CO emissions within a km^2 of the ITO between 2004 and 2006 based on traffic counts and estimates of CO emissions by type of vehicle. The information in Table 2 also suggests that a 34% reduction is highly unlikely. Sharma et al. (2014) estimate total reductions in CO associated with the Delhi Metro to be 1027 tons/year in 2006. Even if the 256,200 tons/year of CO transport emissions were evenly distributed over the NCT, virtually all of the estimated CO reduction due to the Metro would have to occur in the vicinity of the air quality monitor (i.e. within a 2.5 km radius of the ITO monitor) to equal the 34% reduction in ambient CO documented in Goel and Gupta (2017).[20]

Modeling the air quality impacts of the estimated changes in pollutants in Table 2, including the formation of secondary pollutants, requires running a model with full atmospheric chemistry. To our knowledge, this has not been done for Delhi. Guttikunda and Calori (2013) do, however, run a Lagrangian plume model to identify the share of transport emissions in ambient $PM_{2.5}$ in six areas of Delhi in 2010. In South Delhi, a residential area which encompasses Delhi's two ring roads, the authors estimate that 42% of ambient $PM_{2.5}$ in 2010 was due to transport emissions. The Metro was extended to South Delhi in 2018. No study has yet been conducted of the impact of this Metro extension on ambient $PM_{2.5}$ using an air quality model. In the interim, it is important to ground truth econometric estimates by determining (a) what proportion of transport emissions are due to passenger transport; (b) calculating the reduction in emissions from passenger vehicles associated with the Metro.

5. Conclusion

The economics literature on the local air quality impacts of public transport projects is growing rapidly. In this paper we have summarized the econometric methods used to estimate these effects. We have also discussed the approach used by engineers and air quality modelers to estimate the emissions reductions associated with public transport projects, and the likely impact of these emissions reductions on ambient air quality. There are two key insights.

Atmospheric chemistry has important implications for estimating the impact of a transport project, such as Metro rail, on ambient air quality. Reductions in primary pollutants from private or other forms of public transport occur along the road network, as people shift to riding the Metro. The rapid decay of primary pollutants with distance from roads implies that air quality monitors may not capture all the impacts of pollution reductions due to Metro rail (Zhou and Levy, 2007; Karner et al., 2010). This also implies that, for primary pollutants, monitors far from a transit project should be analyzed separately or used for robustness checks but should not be averaged with the readings of monitors near the project. This does not apply to secondary pollutants such as $PM_{2.5}$ or ozone, which travel long distances. This guidance has been applied in the econometric literature to some extent.

It is also important to calculate the likely reduction in emissions resulting from the shift to Metro from other forms of transportation, and to determine in a particular area what percent of total emissions this reduction constitutes. For primary pollutants, a rough rule is that the percentage reduction in emissions in a given area results in an equivalent percentage reduction in ambient concentrations. This should be used as a rough check on whether econometric results of reductions in pollution concentration are reasonable.

CRediT authorship contribution statement

Maureen Cropper: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Palak Suri:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

We declare that we have no potential financial or non-financial conflicts of interest to report.

Data availability

Data will be made available on request.

Appendix

See Table A.1.

[20] If the CO emissions due to transport in Table 2 were evenly distributed over the area of the NCT (approx. 1500 km^2), there would be approximately 3358 tons emitted within a 2.5 km radius of the ITO. For a 34% reduction in CO to occur at the ITO, *all* of the 1027 tons of CO reduced due to the Metro would have to occur within a 2.5 km radius of the ITO.

Table A.1
Additional published studies on the importance of public transit for air quality using econometric methods (Economics or Transportation Journals).

Study	Context	Empirical approach	Pollutants examined	Results
Bel and Holst (2018)	Introduction of Line 1 of BRT Metrobus in Mexico City in 2005	DiD (main) and RD in time (robustness)	Daily averages of CO, NO_x, PM_{10}, SO_2	Decline in CO and NO_x by 6%–7% and in PM_{10} by 8%–9% within 2.5 and 5 km of the BRT corridor compared to 10–30 km away; no effect on SO_2; more rapid decline in CO with distance relative to NO_x and PM_{10}; larger and noisier RD estimates
Gallego et al. (2013)	Transantiago bus routing and scheduling system reform in Santiago, Chile in 2007	Dynamic event study and RD in time	Hourly CO	No immediate effect but a substantial increase in 7 months, likely due to the documented increases in inconvenience under the new system
Bauernschuster et al. (2017)	Strikes affecting Germany's five largest cities' local suburban train connections and the subway-tram-bus network from 2002–11	DiD comparing outcomes in affected and non-affected cities before, during, and after strike episodes	SO_2, CO (examined in a previous version of the paper), PM_{10}, NO_2	Increase in NO_2 by 4.3% of the strike-free level and in PM_{10} by 13.3–14.8%; no effects on SO_2 or CO
Lalive et al. (2018)	Service improvement of regional rail in Germany between 1994 and 2004	Procurement mode (competitiveness) as an instrumental variable for service growth	Annual means of CO, NO_x (estimated by averaging NO and NO_2), SO_2, O_3	10% increase in frequency leads to a weakly significant reduction of 1.9% in NO_x, insignificant reduction in CO, and no effect on SO_2 and O_3
Fageda (2021)	Light rail, tram extensions and introductions in about 98 mid-size European cities across 13 countries between 2008–2016	DiD continuous and binary treatments, rail length and policy indicators respectively	Estimated annual mean PM2.5 from AOD data combined with GEOS-Chem AQM	0.5% decrease in annual estimated $PM_{2.5}$ due to 1% increase in rail coverage; 3% decline in $PM_{2.5}$ in cities due to new rail relative to cities with no rail
Rivers et al. (2020)	Transit strikes in 18 Canadian cities between 1974 and 2011 lasting between 1 to 87 days (average 19)	Event study	Daily and hourly NO_x, CO, $PM_{2.5}$	10% decline in NO_x and no effect on $PM_{2.5}$ and CO due to strikes; likely due to higher NO_x emissions from transit than passenger vehicles
González et al. (2021)	Barcelona Public Transit strikes during 2008–16	Event study	Hourly CO, NO_x, O_3, PM_{10}, and SO_2	Bus strikes lead to higher CO, but no effect on other pollutants, Metro strikes lead to an increase in all pollutants except O_3; regional rail services strikes have ambiguous effects

Note: Main empirical approach is described unless otherwise noted.

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