Subways and Urban Air Pollution*

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Abstract: We investigate the relationship between the opening of a city's subway network and its air quality. We find that particulate concentrations drop by about 5% in a 10km disk surrounding the city center during the year following a new subway system opening. The reduction in particulates is larger nearer the city center, but extends over the whole metropolitan area. The reduction persists over the longest time horizon that we can measure with our data, about eight years, although these estimates are less reliable further from the subway opening date. The 5% percent reduction is consistent with observed ridership in the subway system and induced reductions in automobile travel. Our results also point to decreasing returns to subway expansions, both in terms of particulate reduction and ridership. Using estimates from the literature on the relationship between particulates and infant mortality suggests that each subway rider provides and external health benefit of about 0.64 dollars per trip in the average city over at least the first 5-6 years after system opening. In the absence of pollution pricing, this provides a welfare basis for non-trivial public subsidies to subway ridership.

Key words: subways, public transit, air pollution, aerosol optical depth.

JEL classification: L91, R4, R11, R14

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1. Introduction

We investigate the effect of subway system openings on urban air pollution. We rely on two principal data sources. The first describes the universe of world subway systems. The second is a remotely sensed measure of particulates, Aerosol Optical Depth (AOD), recorded by the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard the Terra and Aqua earth observing satellites between 2000 and 2014. These data allow us to measure airborne particulates everywhere in the world, monthly, with approximately 3km spatial resolution. Our strategy for establishing the causal effect of subways on AOD relies on a comparison of changes in particulates within a city around the time of a subway opening.

The data provides clear evidence of a structural break in an average city's AOD level around the time that it opens its subway network and does not indicate a trend break at any time in our sampling frame. The magnitude of this break is about 5% and is about constant over 48 post-subway months where we observe a constant sample. In fact, the 5% decrease in AOD is evident in all 96 post subway months we observe, although estimates over this longer horizon are less precise and less well identified. Finally, we find that the effect of subway openings declines with distance from the city center, consistent with the fact that subways tend to be concentrated in the central city. We find no evidence that richer, larger, more rainy, or Asian cities respond differently to subway openings. We also find that subway openings have larger effects on AOD and on ridership than do the first expansions, and that the effect of the first expansion is larger than subsequent expansions. That is, surprisingly, there seems to be decreasing returns to scale in the extent of a subway network.

Our findings are important for three reasons. Subways are often proposed as a policy response to urban air pollution. While air pollution consists of many different compounds (particulates PM10, PM2.5, lead, carbon monoxide, sulfur dioxide, nitrogen dioxide, and ozone (O_3)) fine particulates are among the most injurious because they penetrate far into the lungs to cause heart attacks, strokes, lung cancer, and respiratory diseases (Dockery and Pope 1994 and Pope 2000). Indeed, Lelievel et al (Nature 2015) find that PM2.5 leads to more deaths worldwide than any other air pollutant, 3.3 million per year, while a more recent literature documents effects of particulates on labor productivity (Chang et al 2016). Van Donellar et al (2015) find that world wide pollution levels have increased annually at a rate of 2.1% a year from 1998-2012 and that the proportion of the population in East Asia living in areas that routinely exceed WHO guidelines increased from 51% to 70% between 1999 and 2011 while in North America this proportion fell from 62% to 19% over the same period. Against this backdrop, subways figure as an important policy response to particulate pollution. For example, Vollmer Associates, LLP, SYSTRA Consulting, Inc., and Allee King Rosen & Fleming, Inc. (2011) list air pollution reduction as an objective for New York City's 2nd avenue subway expansion. Our analysis provides a basis for assessing their cost effectiveness relative to other remediation policies. Apart from this paper, we are aware of only one study, Chen and Whalley (2012), that measures the effects of subways on air pollution. Like the present investigation, Chen and Whalley (2012) use an event study research design. Unlike the present study, Chen and Whalley (2012) study the opening of a single subway. In contrast, we study all of the 43 subway openings and 104 expansions that occurred anywhere in the world between February 2000 and December 2014. Thus, we dramatically improve on our ability to assess whether subway construction, in fact, reduces urban air pollution.

Second, our estimates of the reduction in pollution following subway openings and expansions, together with estimates of the health implications of particulates from the literature, allow us to calculate the value of averted infant mortality that follows from subway openings and expansions. For an average city in our sample, we estimate that a subway opening averts about 9 infant deaths per year. Using a 6m value of a statistical life, this leads a benefit of about 53m dollars per year. If we normalize the 53m annual value of averted infant deaths by the average number of riders for our sample, we calculate that each subway rider avoids about 0.63 dollars in harm. We estimate the effect of a subway opening on particulates extends at least 5-6 years after system opening, but cannot reject the hypothesis that it is permanent. At a 5% discount rate, the discount present value of this averted harm over five years is about 240m dollars and about 1b dollars if the effect is permanent. These estimates do not include the effects of particulate reduction on morbidity or on mortality in the rest of the age distribution, and so probably understate actual health benefits dramatically.

Only crude estimates of subway capital costs are available. These estimates range from about 1.9 to about 22b dollars for an average system. Thus, for costs at the low end of this range, health benefits from averted pollution may be a significant fraction of construction costs.

Finally, little is known about transportation behavior in developing countries and our research sheds indirect light on this important topic. First, and interestingly, we find no evidence that developing world and developed world cities respond differently to subways. This supports the idea that, at least in this regard, the two classes of cities are similar. Second, a back of the envelope calculation suggests that subways probably account for about a 5% share of trips within a few years of their opening. However, given what is known about the relationship between traffic and PM10 and the between subway ridership and traffic, it seems unlikely that this level of ridership can account for the entire observed 5% reduction in particulates that follows a subway opening. It seems likely that some other mechanism is also at work. We conjecture that subways divert traffic that would otherwise have occurred in particularly dirty cars, at particularly congested times, or that subways reduce the capacity of the road network by encroaching on roads.

2. Literature

While the effects of subways have been studied extensively, these studies have overwhelmingly focused on within-city variation in the relationship between proximity to a subway and housing prices or population density, e.g., Gibbons and Machin (2005) or Billings (2011). There are few studies which, like ours, exploit cross-city variation in subways. Among the exceptions, Baum-Snow and Kahn (2005) study a small sample of US subway systems to examine the relationship between subways and ridership, Voith (1997) also examines a cross-section of cities to investigate the relationship between subways and ridership. Finally, Gonzalez-Navarro and Turner (2016) exploits the same underlying panel data on subway stations that we use here to examine the effect of subway systems on urban population growth over a long term horizon.

To our knowledge, the literature contains only a single paper (Chen and Whalley, 2012) examining the relationship between subways and urban air quality. Chen and Whalley (2012) examine changes in air pollution in central Taipei during the year before and after the opening of the Taipei subway in March of 1996. Chen and Whalley (2012) use hourly pollution measurements from several measuring stations in central Taipei, together with hourly ridership data over the same period. By examining the change in pollution levels around the time of the system opening, Chen and Whalley (2012) estimate an approximately 5%-15% reduction in Carbon Monoxide from the subway opening, about the same effect on Nitrous Oxides, but little effect on either Ozone or particulates.

It is useful to contrast this with our findings. We employ essentially the same research design, but are able to consider 39 cities over a considerably longer time horizon. On the other hand, we are restricted to a single measure of pollution, AOD, and to monthly frequencies. Our results are slightly different. Chen and Whalley (2012) find that the Taipei subway caused a 5-15% reduction in Carbon Monoxide. This encompasses the 5% reduction that we estimate for AOD. However, Chen and Whalley (2012) find no effect on particulates. It is not clear how to reconcile these differences except by pointing out that their confidence intervals are quite large and that pollutants are highly correlated. Unfortunately, the opening of the Taipei subway predates the availability of the remotely sensed AOD data on which our analysis is based so we cannot attempt to replicate the Chen and Whalley (2012) result in our sample.

3. Data

To investigate the effect of subways on urban air pollution we require data for a panel of cities describing subways, air pollution, and control variables. Our air pollution data is based on remotely sensed measures of suspended particulates. Our subways data are the result of primary data collection. We describe these data and their construction below, before turning to a description of control variables.

A *Subways*

We use the same subways data as Gonzalez-Navarro and Turner (2016) organized into a monthly panel. These data define a 'subway' as an electric powered urban rail system that is completely isolated from interactions with automobile traffic and pedestrians. This excludes most streetcars because they interact with vehicle traffic at stoplights and crossings. Underground streetcar segments are counted as subways. The data do not distinguish between surface, underground or aboveground subway lines as long as the exclusive right of way condition is satisfied. To focus on intra-urban subway transportation systems, the data exclude heavy rail commuter lines which in any case tend not to be electric powered. For the most part, these data describe public transit systems that would ordinarily be described as 'subways', e.g., the Paris metro and the New York city subway, and only such systems. As with any such definition, the inclusion or exclusion of particular marginal cases may be controversial.

On the basis of this definition, the data report the latitude, longitude and date of opening of every subway station in the world. We compiled these data manually between January 2012 and February 2014 using the following process. First, using online sources such as `http://www.urbanrail.net/` and links therein, together with links on wikipedia, we complied a list of all subway stations worldwide. Next, for each station on our list, we record opening date, station name, line name, terminal station indicator, transfer station indicator, city and country. Latitude and longitude for each station were obtained from GOOGLE maps. We use the subways data to construct a monthly panel describing the count of operational stations in each subway city between February 2000 and December 2014, the time period for which our air pollution data is available.

171 cities had subways in 2014, 63 in Asia, 62 in Europe and 30 in North America. South America, Australia and Africa together account for the remaining 16. These 171 subway systems consist of 8,889 stations. An average subway system in Asia consists of 55.9 stations, in Europe 51.5 stations, in North America 54.2 and South America 34.6 stations. Subway systems in Europe, North America and Asia are all about the same size, and those in South America are distinctly smaller. On average, the world stock of subway stations increased by about 200 per year and grew by about one third between 2000 and 2014.

Our data on subway systems begins in the 19th century. However, our satellite pollution measures are more recent. Thus, our analysis will rely on subway openings that occurred between 2000 and 2014. Table 1 lists all 43 subway system openings in the world between 2000 and 2014, by date, together with basic information about the cities where they are located. Subways opened fairly uniformly throughout the period and the average opening date is February 2007. An average system opened with 14.4 stations, usually on one line, but sometimes on two or more.

Given our objective of estimating the effect of a subway system opening by examining changes in the pollution level around the time that a city opens its subway system, our analysis hinges on the ability to observe a subway city for some time before and after an opening. We hence face a trade-off between sample size, the length of time we observe cities and maintaining a constant sample of cities to eliminate concerns about sample composition. While we experiment with other study windows, in our primary econometric exercise we will consider the change in AOD in the period extending from 18 months before until 18 months after a subway opening. Since the AOD data runs from February 2000 to December 2014, if we are to base this exercise on a constant sample of cities, we must restrict attention to subways that open between August 2001 and July 2013. In table 1, we see that these are the 39 cities beginning with Rennes and ending with Brescia. In order to consider the longer run effect of subways, in some specifications we consider longer period after the subway opening. In order to do this while maintaining a constant sample of cities for each month, we must drop cities that have openings near the end of the sample.

For 30 of these 43 cities we are able to gather ridership data describing unlinked trips, mostly from annual reports or statistical agencies. Ridership is reported at the monthly level for 19 of these 30. For the other 11, we used linear interpolation to create a monthly level ridership dataset from quarterly or yearly data. Table 1 also reports mean daily ridership for each city where data is available, at the end of the first year of the system's operation. For an average city in our sample, about 97,514 people rode the subway on an average day in the twelfth month of the system's operation.[1]

Figure 1 shows the evolution of ridership as a function of time from opening for the first five years of system operation. The horizontal axis in this figure is months from the opening date. The vertical axis is mean daily ridership per 1000 of city population. We see that ridership increases rapidly over the first few months and then remains about constant for the remainder of the period. This will turn out to be consistent with our findings on the relationship between subway openings and AOD. Except for suggestive evidence of a smaller effect during the six months following system opening, we will find that the effect of subways on AOD is approximately constant over all of the time horizons we examine.

B *Aerosol Optical Depth measurements from the Terra and Aqua earth observing satellites*

The Moderate Resolution Imaging Spectroradiometers aboard the Terra and Aqua Earth observing satellites provide daily measures of aerosol optical depth of the atmosphere at a 3km spatial resolution everywhere in the world (Levy and Hsu et al., 2015*a*,*b*). Remer, Levy, and Munchak (2013) provide a description of how the AOD measure is constructed. Loosely, these instruments operate by comparing reflectance intensity in a particular band against a reference value and attributing the discrepancy to particulates in the air column.[2] The MODIS data are available for download at

[1]We report data sources for ridership data in table A.6.

[2]Formally, Aerosol Optical depth is

$$\text{AOD} = -\ln\left(\frac{\text{light arriving at ground}}{\text{light arriving at top of atmosphere}}\right).$$

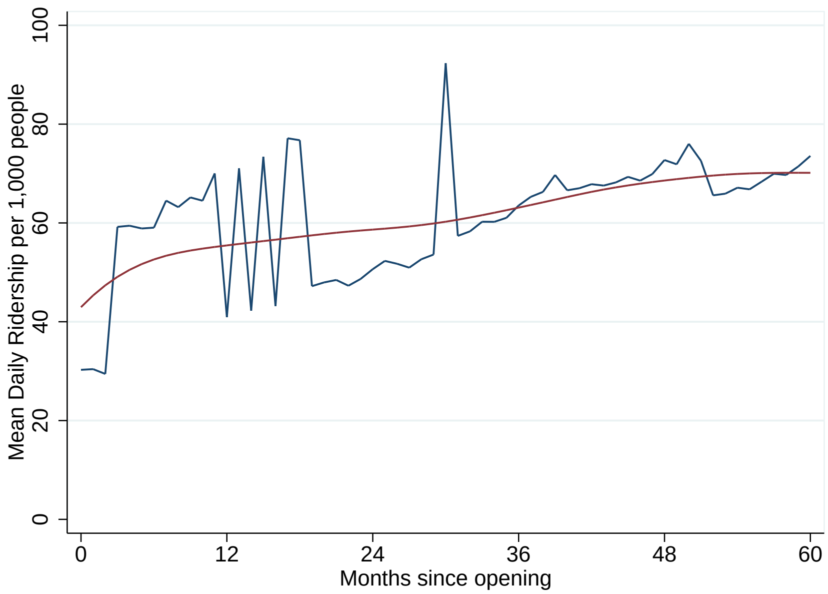
That is, it is a measure of the fraction of incoming light reflected by the air column before reaching the ground. Since at least zero light is reflected by the atmosphere, AOD must be positive and increasing in the share of reflected light (Jacob, 1999, p. 105). The nominal scale of AOD reported by MODIS is $0-5000$, although we have normalized to $0-5$ for legibility.

Table 1: Subway openings between February 2000 and December 2014

City	Opening date	Subway stations	Daily ridership	Mean AOD	SD AOD	City Population	Country GDP PC
Tehran (Iran)	Feb. 2000	8	290,740	0.57	0.18	7,136	13,688
Izmir (Turkey)	Aug. 2000	10		0.30	0.09	2,244	14,200
Istanbul (Turkey)	Sep. 2000	6	64,360	0.32	0.13	8,938	14,200
Brasilia (Brazil)	Mar. 2001	17		0.11	0.07	3,018	10,988
Rennes (France)	Mar. 2002	15		0.22	0.11	283	35,323
Bursa (Turkey)	Aug. 2002	17		0.27	0.09	1,287	14,200
Copenhagen (Denmark)	Nov. 2002	13	69,576	0.19	0.10	1,099	39,784
Porto (Portugal)	Dec. 2002	9	21,951	0.23	0.09	1,266	25,268
Delhi (India)	Dec. 2002	10	117,566	0.88	0.35	17,458	3,300
Dalian (China)	May 2003	12		0.59	0.27	3,148	7,578
Naha (Japan)	Aug. 2003	15	319,033	0.30	0.15	304	34,282
Gwangju (South Korea)	Apr. 2004	13	34,639	0.46	0.23	1,399	28,896
Las Vegas (USA)	Jul. 2004	7	29,078	0.51	0.20	1,560	49,461
Wuhan (China)	Sep. 2004	25		1.01	0.31	7,104	7,578
Shenzhen (China)	Dec. 2004	18	204,944	0.85	0.27	8,382	7,578
San Juan Puerto Rico (USA)	Apr. 2005	16	24,000	0.22	0.11	2,492	49,461
Kazan (Russia)	Aug. 2005	5	46,388	0.24	0.16	1,120	16,583
Nanjing (China)	Aug. 2005	16		0.83	0.31	5,248	7,578
Valparaiso (Chile)	Nov. 2005	20	28,053	0.11	0.03	842	15,657
Turin (Italy)	Feb. 2006	11	23,878	0.31	0.15	1,712	34,604
Daejon (South Korea)	Mar. 2006	12	25,095	0.42	0.25	1,448	28,896
Valencia (Venezuela)	Nov. 2006	3		0.26	0.12	1,554	11,557
Maracaibo (Venezuela)	Nov. 2006	2		0.41	0.17	1,942	11,557
Kaohsiung (Taiwan)	Mar. 2008	36	105,618	0.58	0.24	1,510	7,578
Palma (Spain)	Jul. 2008	9	4,348	0.19	0.07	381	31,424
Lausanne (Switzerland)	Oct. 2008	14	62,638	0.21	0.07	334	48,459
Santo Domingo (DR)	Jan. 2009	16	44,946	0.35	0.19	2,537	9,662
Seville (Spain)	Apr. 2009	21	46,922	0.21	0.08	695	31,424
Seattle (USA)	Jul. 2009	8	20,068	0.17	0.08	3,050	49,461
Dubai (UAE)	Sep. 2009	21	123,980	0.52	0.24	1,739	81,932
Chengdu (China)	Sep. 2010	16		1.01	0.33	6,399	7,578
Shenyang (China)	Sep. 2010	22	279,395	0.55	0.29	5,759	7,578
Chongqing (China)	Jul. 2011	13		0.97	0.24	11,845	7,578
Lima (Peru)	Jul. 2011	16	82,751	0.76	0.23	9,235	7,663
Xian, Shaanxi (China)	Sep. 2011	16	193,324	0.83	0.29	5,437	7,578
Bangalore (India)	Oct. 2011	6	18,433	0.40	0.17	8,879	3,300
Mashhad (Iran)	Oct. 2011	21	75,330	0.53	0.17	2,779	13,688
Algiers (Algeria)	Nov. 2011	10		0.25	0.12	2,489	12,123
Almaty (Kazakhstan)	Dec. 2011	7	16,944	0.32	0.08	1,452	13,698
Suzhou, Jiangsu (China)	Apr. 2012	24	126,335	0.87	0.27	4,614	7,578
Kunming (China)	Jun. 2012	14		0.35	0.27	3,564	7,578
Hangzhou (China)	Nov. 2012	31	305,314	0.85	0.23	5,798	7,578
Brescia (Italy)	Mar. 2013	17	40,719	0.32	0.15	455	34,604
Average	Feb. 2007	14.4	97,514	0.46	0.18	3,719	20,011

Stations and daily ridership reported 12 months after opening. Mean and SD AOD columns report mean and standard deviation values in a 10km radius circle using Terra satellite monthly observations from 2000-2014. Metropolitan area population in thousands. Country GDP per capita from PWT. For Palma (Spain), subway originally began service in April 2007 but was almost immediately shut down for major repairs. It reopened in July 2008. We use the latter as the starting date. San Juan (Puerto Rico) opened in trial mode with partial service in December 2004, with full service being implemented from April 2005. We use the latter as the starting date.

Figure 1: Daily ridership per capita



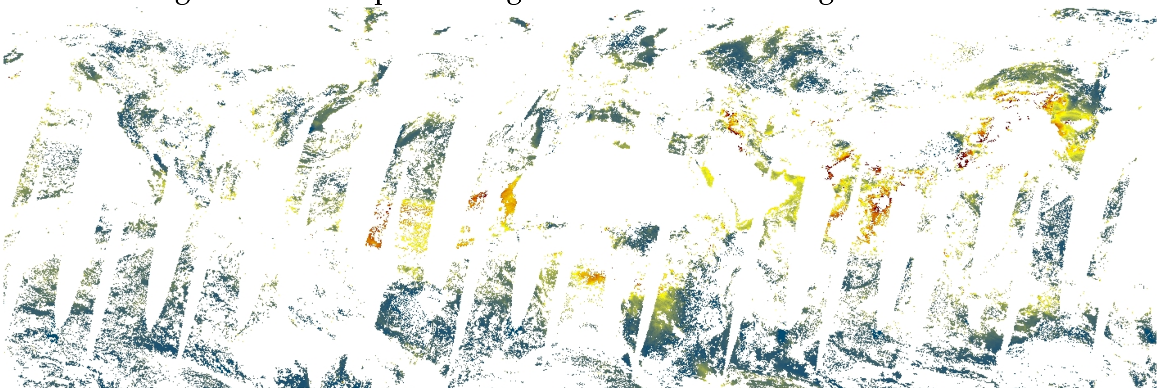
Note: Graph depicts average daily passengers on subway per 1,000 people in metropolitan area, as well as a locally weighted regression of the series.

`ftp://ladsweb.nascom.nasa.gov/allData/6/`. Data is available in 'granules' which describe five minutes of satellite time. These granules are available more or less continuously from February 24, 2000 until December 31, 2014 for the Terra satellite, and from July 4, 2002 until December 31, 2014 for Aqua. That is, the complete Terra and Aqua data consists of about 1.6m granules. During January of 2016, we downloaded all available granules and subsequently consolidated them into daily rasters describing global AOD. Each of these daily aggregates describes about 86m pixels covering the earth in a regular grid of 3km cells. With 28 satellite years of daily observations, this means that our monthly AOD data results from aggregating about 850b pixel-day measurements of AOD. The data appendix describes our processing of these data in more detail.

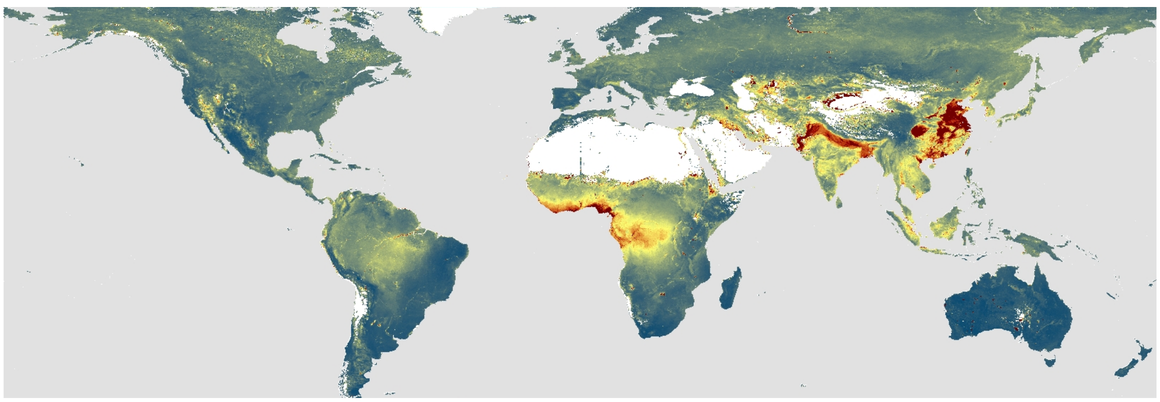
With daily images in hand, it is straightforward to construct monthly averages. The top panel of figure 2 shows the resulting images for the entire world for June 1, 2014 and the bottom panel shows average AOD over 2000 to 2014, both from the Terra satellite. Darker colors indicate higher AOD readings. Unsurprisingly, the figures show high AOD in India and China. Myhre et al (2008) attribute high AOD over Central and Western Africa to anthropogenic biomass burning in the region. White areas indicate missing data. Because they are highly reflective, the algorithm for recovering AOD from reflectance values performs poorly over light surfaces, so missing data is common in desert regions and over snow (Levy, Mattoo, Munchak, Remer, Sayer, Patadia, and Hsu, 2013).

The MODIS instrumentation can only record AOD on cloud free days. In the June 1 image, much of the missing data reflects cloud cover, though some reflects the fact that TERRA's polar orbit

Figure 2: Two maps showing AOD. Red indicates higher levels of AOD



Aerosol Optical Depth, June 1st, 2014 Terra



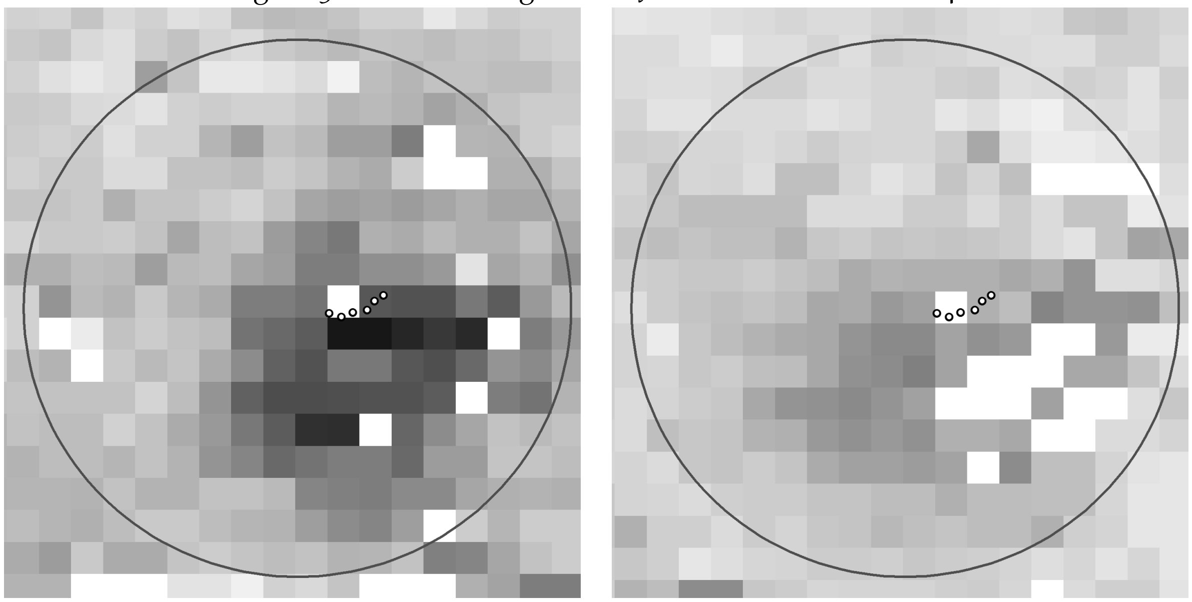
Aerosol Optical Depth, Average 2000-2014, Terra

brings it over most, but not all of the earth's surface each day. Because AOD reporting is sensitive to cloud cover and light surfaces, there is seasonality in the MODIS data. We see more missing data in the Northern Hemisphere in the Winter than the summer. The counter-cyclical Southern Hemisphere phenomena also occurs but is less dramatic.

Figure 3 illustrates the AOD data for particular cities. Panel (a) illustrates the AOD data for Bangalore in June of 2014. To show scale, the large circle in this image is 10km in radius. Bangalore is noteworthy in two regards. First, there are relatively few pixels for which we have no AOD reading over the month. Second, there is a wide range in AOD readings at this scale of observation. The corresponding picture for Delhi is entirely black. Panel (b) provides the corresponding image for Bangalore in December 2014.

We construct the monthly images presented in figure 3 by averaging within each pixel over the course of a month. This means that, if we were to average over an area in the monthly images, a pixel which we observe only once during the month would receive the same weight as one that we observe many times. Therefore, to calculate city level monthly AOD measure, we instead average over a whole disk centered on the city for each day, and then average these city day measures, weighting by the number of pixels observed in each day. Thus, our measure of AOD within 10km of the center of a city is an average of all pixel-days of AOD readings that fall in this region during

Figure 3: AOD for Bangalore in June and December 2014



(a) Bangalore, June 2014 (b) Bangalore, December 2014

Terra AOD for Bangalore in June and December of 2014. The large circle in each image has a radius of 10km and is centered on each city's central business district. Subway stations as of December 2014 are shown as black circles. Darker values indicates areas where AOD is larger and white indicates missing values.

the month.

Table 1 reports the mean and standard deviation of AOD for each of our 43 cities using the Terra satellite. Table 2 provides more detail. In 2014, the average AOD reading within 10km of a city center from the Aqua satellite was 0.42. It was higher in Asian cities, 0.56, and dramatically lower in European and North American cities. The corresponding reading from Terra is slightly higher. The top panel of table 2 also reports AOD measurements based on disks with radius 25km centered on each city. Unsurprisingly, these larger disks have slightly lower AOD levels than the smaller and more central 10km disks. As for the 10km disks, AOD measures based on Terra are slightly higher than those for Aqua, and Asian cities are more polluted than non-Asian cities.

In an average month, the AOD reading for an average 10km city disk is based on 109 pixel-days for Aqua and 123 for Terra. Since the pixels are nominally 3km, if all possible pixel days in a 10k disk were recorded over a month, we would expect about $(365/12) \times \pi \times (10km/3km)^2 = 1061$ pixels. Thus, conditional on observing one or more pixel days, our city-month AOD values are based on measurements of about 10% of possible pixel days. About 10% of city-months contain zero pixel day observations and do not appear in our sample. An average AOD reading in a 25km disk is based about 9 times as many pixel-days as the smaller 10km disks. Since the area covered by these disks is only about 6 times as large, we record a higher proportion of possible measurements in the large disks. We suspect that this reflects two factors. First, that the satellites may be worse measuring AOD over highly reflective built environments, and so do worse over more densely built up central cities. Second, pixels are included in a disk on the basis of their centroid location, and this makes it easier for the smaller disks to 'just miss' including pixels.

The second two panels of table 2 present AOD averages for 2007 and 2000 for 10 and 25km disks. Because only the Terra satellite was in operation in 2000, the third panel presents only these measures. The patterns that we saw in 2014 persist in the other years. Terra shows higher readings than Aqua, 25k AOD is smaller than 10k and Asian cities are more polluted than the rest of the world. Comparing across years, we see that variation across years is small compared to the level and compared to variation across continents. Table 2 suggests a slight downward trend in European and North American AOD, a slight upward trend in South American and Asia, and no obvious trend in the 43 cities as a whole.

Figure A.2 illustrates the extent of satellite coverage for our sample of 43 subway cities. Panel (a) shows the count of cities by month for which we observe AOD in a 10km disk surrounding the city's center for each of the two MODIS satellites. Panel (b) plots mean AOD for 10km disks centered on the central business districts of our 43 subway cities. Both figures show a strong seasonal pattern in AOD. This reflects seasonal variation in cloud cover and motivates our use of city-by-month indicators in all of our regressions.

Together the two panels of figure A.2 suggest that a relationship exists between the extent of coverage and the level of AOD. In fact, regression AOD in a city month disk on the count of pixel days used to calculate that average reveals a slightly positive relationship. We conjecture that this reflects the fact that the air is cleaner in rainy places where cloud cover is more common. Regardless of the reason, we have experimented broadly with sampling rules that reduce the importance of city-months for which AOD data is sparse and with controlling for the count of pixel days used to construct each city month average. In most of our regression results we control for the number of pixel-days used to construct each city-month AOD observation, but do not discuss the issue further.

C *Other control variables*

In section 4 we validate the relationship between the MODIS data and ground based measurements in our sample. Consistent with the large related literature, which we describe in section 4, we find that local weather conditions are important determinants of MODIS AOD. Given this, we construct several controls for city-month weather conditions. The CRU gridded dataset (Harris, Jones, Osborn, and Lister, 2014) provides high-resolution monthly climatic data describing cloud cover percentage, frost day frequency, mean temperature, precipitation, and vapour pressure. We use these data to calculate monthly and annual averages of these variables over disks centered on each city. These are our 'climate controls'.

Table 2: AOD in 43 new subway cities

	World	Africa	Asia	Europe	North A.	South A.
Subway openings since 2000	43	1	25	8	4	5
2014						
Av. AOD (Aqua), 10km	0.42	0.20	0.56	0.18	0.26	0.31
Av. AOD (Terra), 10km	0.45	0.23	0.59	0.21	0.28	0.3
Av. # pixels (Aqua), 10km	109.04	242.21	98.68	170.03	51.49	75.06
Av. # pixels (Terra), 10km	123.64	255.94	114.41	183.55	56.84	96.26
Av. AOD (Aqua), 25km	0.37	0.17	0.51	0.15	0.19	0.23
Av. AOD (Terra), 25km	0.41	0.20	0.55	0.18	0.20	0.26
Av. # pixels (Aqua), 25km	989.77	2269.21	914.96	1436.29	672.48	637.03
Av. # pixels (Terra), 25km	1080.92	2418.59	1016.73	1522.35	568.57	820.31
2007						
Av. AOD (Aqua), 10km	0.44	0.26	0.57	0.22	0.32	0.3
Av. AOD (Terra), 10km	0.48	0.29	0.63	0.24	0.33	0.29
Av. AOD (Aqua), 25km	0.39	0.22	0.53	0.19	0.22	0.24
Av. AOD (Terra), 25km	0.43	0.25	0.58	0.21	0.23	0.27
2000						
Av. AOD (Aqua), 10km	.	.	.	.	.	.
Av. AOD (Terra), 10km	0.43	0.27	0.54	0.28	0.34	0.29
Av. AOD (Aqua), 25km	.	.	.	.	.	.
Av. AOD (Terra), 25km	0.38	0.23	0.49	0.24	0.22	0.23

We also include city population and country GDP per capita to characterize the level of economic activity of each city. Our population data comes from the United Nation's 2014 Revision of the World Urbanization Prospects (DESA Population Division, 2014). These data describe annual population counts for all urban agglomerations with populations exceeding 300,000 at any time between 1950 and 2014 and also provide coordinates for the centers of all of the cities it describes. With a few exceptions, which we adjusted by hand on the basis of lights at night data, we use these coordinates for the centers of all of our cities. We use the Penn World Tables to obtain annual measures of country GDP (Feenstra, Inklaar, and Timmer, 2015) for all cities in our sample.[3] We interpolate the annual GDP and population data to construct monthly measures.

Table 1 reports population and country level GDP per capita for each city where a system opened in the 12th month after opening. We see in table 1 that cities that open subways are large, their average population is 3.7m, and tend to be in middle to high income countries.

Table 3: The relationship between AOD and ground-based particulate measures

	PM10			PM2.5		
	(1)	(2)	(3)	(4)	(5)	(6)
Terra AOD	112.3***	93.1***	61.1***	53.0*	27.8***	21.9***
	(12.0)	(11.4)	(10.7)	(28.4)	(5.4)	(5.9)
Constant	1.6	109.7**	94.8**	1.3	68.7***	183.524***
	(3.6)	(42.3)	(40.3)	(7.8)	(24.9)	(41.7)
Mean dep. var.	44.85	44.85	45.13	17.39	17.39	17.41
Mean indep. var.	0.39	0.39	0.39	0.30	0.30	0.30
R-squared	0.50	0.77	0.83	0.26	0.90	0.94
Cities	137	137	137	79	79	79
N	221	221	218	128	128	127
Aqua AOD	116.1***	98.9***	65.5***	54.4*	27.0***	20.4***
	(12.7)	(12.8)	(11.7)	(31.5)	(6.5)	(7.1)
Constant	3.6	105.4**	91.2**	2.5	60.6**	195.0***
	(3.6)	(48.5)	(42.1)	(7.8)	(27.1)	(52.2)
Mean dep. var.	44.85	44.85	45.13	17.39	17.39	17.41
Mean indep. var.	0.36	0.36	0.36	0.27	0.27	0.28
R-squared	0.49	0.76	0.82	0.21	0.89	0.93
Cities	137	137	137	79	79	79
N	221	221	218	128	128	127

Note: Aerosol Optical Depth is the mean value in a 10km disk around the city center. Columns (1) and (4) have no control variables. Columns (2) and (5) add climate controls and continent × year dummies. Columns (3) and (6) add controls for city population and country GDP. Robust standard errors in parentheses. Stars denote significance levels: * 0.10 ** 0.05 *** 0.01.

4. Aerosol Optical Depth versus ground based measurements

A series of papers compare measures of AOD to measures of particulate concentration from surface instruments (Kumar, Chu, Foster, Peters, and Willis, 2011, Gupta, Christopher, Wang, Gehrig, Lee, and Kumar, 2006, Kumar, Chu, and Foster, 2007) in particular, examines the ability of AOD to predict particulates in a set of large cities, several of which are subway cities.

Broadly, this literature concludes that AOD is a good measure of airborne particulates, with two caveats. First, satellite reports of AOD describe daytime average conditions over a wide area at the particular time the satellite passes overhead, while ground based instruments record conditions at a particular location, often over a period of hours. This causes an obvious divergence between satellite and ground based measures. In addition, ground based instruments report the concentration of dry particulates, while the satellite based measure has trouble distinguishing

[3]Two of our subway cities, Algiers and Dubai, lie in countries, Algeria and UAE, for which the Penn World Tables do not provide GDP. For these two cities, we use country level GPD information downloaded from the World Bank.

water vapor from other particles. This suggests that some method of accounting for differences in climate will be important when we examine the relationship between subways and AOD.

As a direct check on our AOD data, we take advantage of World Health Organization data (World Health Organization, 2014) describing average annual PM10 and PM2.5 concentrations (μg/m^3) in a set of 398 cities for which they could collect ground monitoring based data obtained between 2003 and 2013. Of the 398 cities, 9 are observed in three years, 227 in two years and 162 in just one year. Not all city-years record both PM10 and PM2.5. We are able to match 221 city-years of the WHO PM10 and 128 city-years of the PM2.5 data to our subway cities data.

We can now compare the WHO ground based annual measures of particulates to annual averages of MODIS AOD measurements in subway cities. Specifically, we conduct the following regressions

$$\text{PM}_{yit} = \alpha_0 + \alpha_1 \text{AOD}_{it} + \text{Controls}_{it} + \epsilon_{it},$$

where $y \in \{2.5, 10\}$ is particulate size, i refers to cities and t refers to years for which we can match WHO data to our AOD sample.

Table 3 reports results. The first column presents the results of a regression of the WHO measure of PM10 on annual average Terra AOD within 10km of a subway city center. There is a strong positive relationship between the two quantities and the R^2 of the regression is 0.50. The AOD coefficient of 112.3 in column 1 means that a one unit increase in AOD maps to a 112.3 μg/m^3 increase in PM10. From table 2, we see that Terra 10k readings for North America decreased by 0.06 between 2000 and 2014. Multiplying by 112.3 this gives a about a 7μg/,^{3} decrease. By contrast, according to US EPA historical data, during this same period US average PM10 declined from 65.6 to 55.0 μg/m^3 , or about a 10 unit decrease.[4] Since table 2 reflects four cities in North America with new subways, while the EPA reports area weighted measures for the US, this seems reasonably close.

In column 2, we conduct the same regression but include linear and quadratic terms in our annual climate variables, counts of AOD pixel-days, and year-by-continent indicators. The coefficient on AOD drops by about 1.5 standard errors, from 112 to 93, and the R^2 increases to 0.78. In column 3, we add controls for city population and country GDP. This decreases the coefficient on AOD to 61 and increases the R^2 of the regression to 0.83. Columns (4) to (6) replicate (1) to (3) but use PM2.5, as the dependent variable. The results are qualitatively similar. We conduct, but do not present, corresponding regressions where the dependent variable is based on Aqua rather than Terra and where our AOD measure is based on a 25km ring around the city center instead of 10km. All results are broadly similar.[5]

[4] `https://www.epa.gov/air-trends/particulate-matter-pm10-trends`, accessed April 3, 2017.

[5] We note that the results in table 3 are quite different from those on which the 2013 Global burden of disease estimates are based (Brauer, Freedman, Frostad, Van Donkelaar, Martin, Dentener, Dingenen, Estep, Amini, Apte *et al.*, 2015). In particular, they estimate

$$\ln(\text{PM2.5}) \approx 0.8 + 0.7 \ln(\text{AOD}).$$

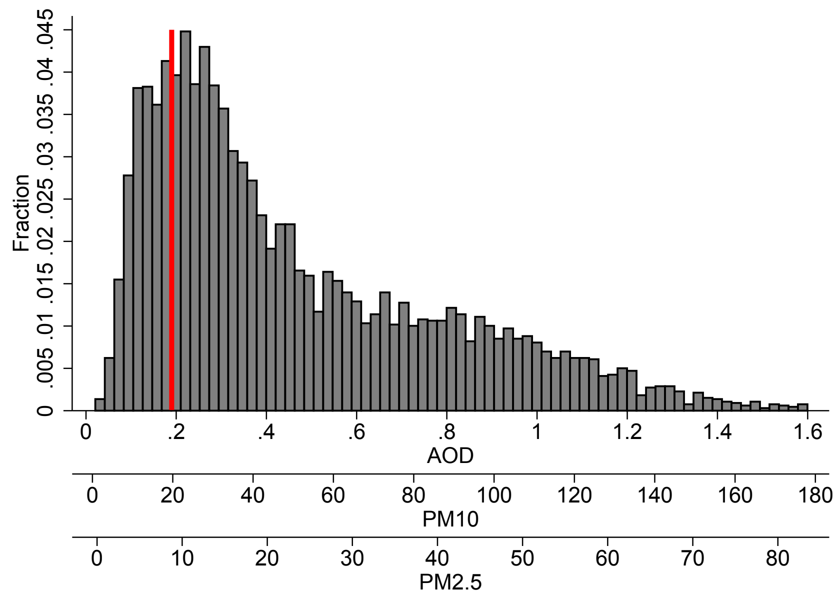
Recall that the ground-based instruments and MODIS, in fact, measure something different. Ground-based instruments measure pollution at a point over an extended period of time. Remote sensing measures particulates across a wide area at an instant. Given this difference, the extent to which the two measures appear to agree seems remarkable. In addition to validating the use of remotely sensed AOD, table 3 provides a basis for translating our estimates of the relationship between subways and AOD into a relationship between subways and PM2.5, or PM10. To illustrate this process, and to help to describe our data, figure 4 provides a histogram of the 12,169 city-months used for our main econometric analysis. The figure provides three different scales for the horizontal axis. The top scale is the native AOD measure. The second two axes are affine transformations of the AOD scale into PM10 and PM2.5 based on columns 1 and 3 of table 3. For reference, the red line in the figure gives the World Health Organization recommended maximum annual average PM10 exposure level (20 μg/m^3). Apart from providing intuition about our data, this facilitates the use of estimates of the health effects of PM10 or PM2.5 to value changes in AOD that follow from subway openings.

5. The relationship between subway system openings and AOD

In our primary econometric exercise, we examine changes in AOD around the time that a city opens its subway system. Let $i = 1,...,I$ index subway cities and t index months between February 2000 and December 2014. Thus, AOD_{it} denotes AOD in city i at time t. We are interested in changes to AOD in the months around a system opening. If city i opens its subway in month t', then define $\tau_{it} = t - t'$. That is, τ_{it} is 'months since the subway opened', with months before the opening taking negative values. Let k describe the window over which we analyze AOD, i.e., $\tau_{it} \in \{-k,...,0,...,k\}$. We will most often be interested in the case of $k = 18$, that is, the 37 month period extending from 18 months before until 18 months after a subway opening. There are 39 cities that open a subway for which this entire window falls within the February 2000 to December 2014 range of our AOD data. In order to keep a constant sample of cities for each month, we most often consider this set.

Comparing with table 3, we see that these coefficient estimates are quite different. The difference reflects primarily our use of the level of PM2.5, rather than its logarithm, as the dependent variable. We also use the level of AOD rather than its logarithm as the explanatory variable. Since AOD is typically around 0.5, this turns out not to be important. Finally, our sample describes a different and more urban sample of locations, relies on annual rather than daily data, and measures AOD using just MODIS data rather than an average of MODIS and a measure imputed using a climate model and ground based emissions release information. We prefer the formulation in table 3 to that in Brauer *et al.* (2015) for three reasons. First, AOD is already a logarithm (see footnote 2), so the Brauer et al. specification uses the logarithm of a logarithm as its main explanatory variable. Second, mortality and morbidity estimates are typically based on levels of pollutants, not on percentage changes, so the dependent variable in our regressions is more immediately useful for evaluating the health implications of changes in AOD. Finally, we control for weather conditions, which appears to be important. In any case, the R^2 in both studies is of similar magnitude.

Figure 4: Distribution of AOD across city-months



Note: Histogram of city-months by AOD, PM10 and PM2.5. PM10 and PM 2.5 axes rescaled from AOD using columns 1 and 3 of table 3. Red line indicates WHO threshold level for annual average PM10 exposure

Now define the following families of indicator variables,

$$D_{it}(j) = \begin{cases} 1 & \tau_{it} = j \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

$$D_{it}(j,j') = \begin{cases} 1 & \tau_{it} \in \{j,...,j'\} \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

$$D_{it}(j \lesseqgtr j') = \begin{cases} 1 & \tau_{it} \lesseqgtr j' \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

Equation (1) describes indicators for sets of city-months that are the same number of months away from the month when their subway system opens. Equation (2) describes indicators for each a set of step functions beginning j and ending in j' months from the subway opening month. Finally, equation (3) describes indicators for city-months that are far enough from the subway opening date that they fall outside our study window.

Sections 3 and 4 indicate the following patterns in the data. The AOD data are seasonal and the pattern of seasonality varies across the globe. The AOD measurements reported by Terra are systematically larger than Aqua, but otherwise the two satellites track each other very closely. Remotely sensed AOD may confound water vapor with anthropogenic particles. City-month AOD averages are slightly decreasing in the number of pixel-days on which they are based. Finally, there are long run trends in pollution, and these trends are probably different on different continents. Given this, we include the following controls in our regressions; a satellite indicator, year-by-continent indicators, and city-by-calendar month indicators. We include the count of AOD pixel-days used to calculate the city-month AOD and linear and quadratic terms of our monthly climate variables. Finally, the control set sometimes includes linear and quadratic terms in country level GDP and city level population. Subject to the change from an annual to monthly period of observation, these control variables closely correspond to those we used in our investigation of the relationship between PM10, PM2.5 and AOD in table 3. Controls for city-months (i.e. June in Delhi) are particularly important since they capture city-specific pollution patterns across months due to factors such as seasonal wind patterns. Without these controls for city specific seasonality we are not able to detect an effect of subways.

Following Andrews (1993), Andrews (2003) and Hansen (2000), we check for a structural break in the value of AOD around the time of system opening by estimating a series of regressions of AOD on a step function as we allow the timing of the step to traverse the study period. The relevant regressions are,

$$\begin{aligned} AOD_{it} &= \alpha_0 + \alpha_{1j}\, D_{it}(j,k) \\ &\quad + \alpha_2\, D_{it}(\tau < -k) + \alpha_4\, D_{it}(\tau > k) + \text{controls}_{it} + \epsilon_{it} \\ &\quad \text{for all } j \in \{-0.75k,...,0,...,0.75k\} \end{aligned} \tag{4}$$

For our main analysis we set $k = 18$. This window length strikes a balance maintaining the number of cities from which we identify our coefficient of interest and having a long analysis window. This implies we use of a 37 month study window[6] and estimate equation (4) for each month in $j \in \{-14,...,14\}$ with errors clustered at the city level. We then calculate a Wald test of $\alpha_{1j} = 0$ for each j.[7] By including pre- and post-period indicators in these regressions we use all city-months in our sample to estimate city-month indicators, continent-year indicators and climate variables, while only using AOD variation near the subway opening date to identify the effects of subways on AOD. Panel (a) of Figure 5 plots these test statistics.

The figure shows a clear pattern. Wald statistics increase from low level to a peak right after the subway opening, before quickly falling. That is, this plot suggests that subway system opening leads to break in the AOD sequence, and that this break occurs when the system opens. [8]

On the basis of Panel (a) of Figure 5, we assume a break in AOD levels that coincides with the first full month of subway system operations, i.e., $\tau = 1$. Conditional on such a break, we next check for a change in the trend of AOD associated with subway openings. We proceed much as in

[6] (18*2+1) months.

[7] Absent clustering, this Wald test coincides with an F test.

[8] Andrews (2003) gives (asymptotic) critical values for the test statistic values we have just generated, a 'sup-Wald' test for $\alpha_{1j} = 0$ for all j. For our case, where the break in question affects only one parameter and where we trim 25% from the boundaries of the sample, the 1% critical value of this statistic is 11.5, less than the value of 15.14 that we observe for the Wald statistic in the month after a system opening. With this said, our estimation framework differs from the one for which this test statistic is derived in several small ways, and so we regard this test with some caution.

Table 4: Subway opening and AOD for 18 month period post system opening

	(1)	(2)	(3)	(4)	(5)	(6)
1-18 months post	-0.0205**	-0.0211**	-0.0201**	-0.0209**	-0.0213**	-0.0221**
	(0.00931)	(0.00957)	(0.00883)	(0.00894)	(0.00815)	(0.00861)
city pop.& GDP	No	Yes	No	Yes	No	Yes
city-level trends	No	No	Yes	Yes	No	No
city-level pre/post trends	No	No	No	No	Yes	Yes
Mean dep. var.	0.457	0.457	0.457	0.457	0.457	0.457
R-squared	0.833	0.834	0.838	0.838	0.839	0.839
Number of events	39	39	39	39	39	39
N	12,169	12,169	12,169	12,169	12,169	12,169

*Note: Dependent variable is monthly mean AOD in a 10km disk centered around the city center for a constant sample of cities. Standard errors clustered at the city level in parentheses. All regressions include the following controls; linear and quadratic climate controls (temperature, vapor, cloud cover, precipitation, frost days), AOD pixel count, satellite indicator, calendar month-city indicators, year-continent indicators, pre- and post-period indicators. Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.*

our test for a break, but instead look for a change in trend around the time of a subway opening. Formally, this means estimating the following set of regressions,

$$\begin{aligned} AOD_{it} &= \alpha_0 + \alpha_1 \tau_{it} + \alpha_{2j} \tau_{it} D_{it}(j,k) + \alpha_3 D_{it}(1,k) \\ &\quad + \alpha_4 D_{it}(\tau < -k) + \alpha_5 D_{it}(\tau > k) + \text{controls}_{it} + \epsilon_{it} \\ &\text{for all } j \in \{-0.75k,...,0,...,0.75k\} \end{aligned} \tag{5}$$

As before, we estimate the regression (5) for each month in $j \in \{-14,...,14\}$ with errors clustered at the city level and calculate the Wald test for $\alpha_2 = 0$ for each regression.[9] Panel (b) of Figure 5 plots these Wald statistic values as j varies. [10] Thus, conditional on a step at $\tau = 1$, subways openings do not seem to cause a change in the trend of AOD in a city.

Figure 5 suggests that subway openings cause a one time shift in a city's level of AOD, and no other change in the evolution of AOD. Given this evidence for the existence and timing of an effect of subway openings on the evolution of AOD, we turn to estimating its size.[11]

To illustrate patterns in the data, we also estimate,

$$\begin{aligned} AOD_{it} &= \alpha_0 + \sum_{j \in \{-k,...,k\} \setminus \{0\}} \alpha_{1j} D_{it}(j) \\ &\quad + \alpha_2\, D_{it}(\tau < -k) + \alpha_3\, D_{it}(\tau > k) + \text{controls}_{it} + \epsilon_{it} \end{aligned} \tag{6}$$

[9] An alternative would be to simultaneously search for locations of the break and trend break. Hansen (2000) argues that sequential searching, as we do, arrives at the same result.

[10] All values are well below the 10% critical value of 6.46 given in Andrews (1993). Again, our framework differs from the framework under which this test statistic is derived so this test should be regarded with caution.

[11] Hansen (2000) provides an elegant method for estimating the location and size of the break along with confidence intervals. This method assumes a balanced panel, and so we have not been able to apply it to our data.

Control variables are the same as those used in our test for a structural break. Since the indicator for $\tau_{it} = 0$ is omitted, the α_{1j} measure mean difference in AOD for city-months with $\tau_{it} = j$ from those with $\tau_{it} = 0$. Figure 5 plots as dots the 36 monthly values of α_{1j} that result from conducting regression (6) with $k = 18$. The vertical axis of this figure indicates AOD. From table 2, sample mean AOD is about 0.44, so monthly variation in AOD is small relative to the mean level. Inspection of figure 5 suggests a drop in AOD around the time of a system opening.

To estimate the size of the post-subway drop in AOD, and to investigate its robustness, we conduct regressions of the following form,

$$\begin{aligned} AOD_{it} = {} & \alpha_0 + \alpha_1 D_{it}(1,k) \\ & + \alpha_2 D_{it}(0) + \alpha_3\, D_{it}(\tau < -k) + \alpha_4\, D_{it}(\tau > k) + \text{controls}_{it} + \epsilon_{it}. \end{aligned} \tag{7}$$

This is a regression of AOD on an indicator for post-opening and controls. As before, we include pre- and post-period indicators in order to isolate AOD variation for city-months close to the time of their subway opening. We include a dummy variable for city-months when $\tau_{it} = 0$. This month is 'partly treated' and this specification ignores AOD variation for these partly-treated city-months. The intercept, α_0, gives the conditional mean AOD over the city-months where $\tau_{it} \in \{-18,..., -1\}$. The coefficient of interest is α_1, the difference in conditional mean AOD between city-months with $\tau_{it} \in \{-18,..., -1\}$ and those with $\tau_{it} \in \{1,...,18\}$.

Table 4 presents results. In column 1 of table 4 we conduct the regression given in equation (7) with our basic set of controls. We see that the effect of subways on AOD in the 18 months following a subway opening, α_1, is about -0.02 and is different from zero at the 5% level. Column 2 adds country level GDP and city population. Column 3 adds city specific trends. Column 4 adds country level GDP and population and city specific trends. Column 5 adds city specific trends and allows for a trend break in each city at time zero. Column 6 adds country level GDP and population to the specification of column 5. The estimated effect on AOD of subway opening is stable across these various specifications. The difference between the smallest and largest coefficients (columns 3 and 6) is 0.002. This is about 25% of the standard error of the most precise estimate in column 5. Panel (c) of figure 5 shows the magnitude of the AOD coefficient from column 2, as well as 95% confidence bounds.

Table 4 strongly suggests that opening a subway network decreases a city's AOD by about 0.02 over the 18 month period following the opening. From table 2, the sample mean value of AOD is about 0.43, so this 0.02 subway effect on AOD is about a 5% reduction for an average city.

Regression results so far focus on average effects over the 18 months before and after a subway opening. Table A.1 refines the results of table 4 by decomposing the study window into 6 month bins. These estimates are broadly consistent with inspection of panel (c) of figure 5 and table 4. Subways have a negative effect on AOD during each six month period following a subway opening. These effects are largest during the period from 7-12 months after an opening. Unsurprisingly, our estimates are somewhat imprecise, and only the effect during the 7-12 months post-opening is distinguishable from zero at conventional confidence levels. Estimates of the subway effect on AOD in the two pre-periods are dramatically smaller than post-periods, but are estimated with about the same precision. In particular, and reassuringly, they are not distinguishable from zero. This suggests there is no ramp-up in AOD before subway openings that would be a threat to identification.

A *Longer time horizons*

Subways are durable and their effects probably extend over decades. Hence, it is of interest to extend our estimates of the effects of subways to the longest possible horizon that our data permit. Unfortunately, considering a longer treatment period requires that we degrade our research design in one of two ways. As we consider longer treatment periods we must either allow later post-treatment effects to reflect a decreasing set of cities, opening the door to confounding composition with subway effects, or else restrict attention to progressively smaller samples of cities, reducing precision and raising questions of external validity. In spite of this, the importance of obtaining estimates over a time horizon that more nearly approximates the planning horizon suggests that such estimates will be useful, even though we have less confidence in them.

In table 5 we continue to consider a pre-treatment period beginning 18 months before an opening, but consider longer post-treatment periods. In columns 1 and 2 we consider two years after an opening, and allow the subway effect to vary by year using a specification that is otherwise the same as we used in table 4. As in table 4, the two columns differ only in that column 2 includes controls for city population and country level GDP, while column 1 does not. We see that the one year effect is about -0.02, statistically identical to our estimate of the 18 month effect in table 4. Point estimates of the second year effect are slightly smaller and are estimated with about the same precision as the 1 year effect. We can reject neither the hypothesis that the second year effect is zero nor that it is the same as the one year effect. In order to extend our sample to two years post-treatment with a constant sample of cities in all months, we lose a city and the first two columns of table 5 reflect 38 subway openings instead of 39.

In columns 3 and 4 of table 5 we extend the post-treatment period to 36 months. Each of the three post treatment years are negative and estimated precisely enough that they can be distinguished from zero. Point estimates are slightly increasing in magnitude with time from the system opening, although the change is not large relative to the magnitude or precision of the estimates. To consider the three year post-treatment period with a constant sample of cities in each month, we restrict our sample to 35 cities. Thus, the slight change in the year 1 and 2 treatments from columns 1 and 2 to columns 3 and 4 may reflect the change in specification or the change in sample. Finally, columns 5 and 6 consider a four year post-treatment period. These columns indicate slightly larger effects than in the other columns, and suggest that the effect of subways increases over time, although the precision of these estimates does not allow us to reject the hypothesis that the effect is constant in all post-treatment years. To preserve a constant sample of cities over this longer horizon, we restrict our sample to only 28 subway openings.

Table 6 extends the analysis horizon by dropping the requirement that the sample of cities is constant throughout the window of analysis and allows us to show estimates of the effect of subways over the five to eight years after a system opening. To begin, columns 1 and 2 of table 6 look at the effect of subways on five year post-treatment period following the specification of column 2 of table 4 except for the longer treatment period. For reference, column 1 restricts attention to set of 26 cities for which we observe the entire post-treatment period.[12] In column 1 we see that all yearly effects are different from zero and are statistically different from zero, but, except for the very large effect in the fifth year, not from our baseline estimate of about 0.02. Switching to the larger sample of 39 cites in column 2, we see that coefficient magnitudes and standard error decrease slightly. In columns 3 to 5, we consider progressively longer treatment periods.

Inspection of these results reveals three patterns. First, across specifications, point estimates are within 1.64 standard errors of -0.02 in almost all cases. Second, only the first and fifth year effect are significantly different from zero and the fifth year effect seems anomalously large relative to the other years. Finally, there is no obvious trend in coefficient magnitudes with time from opening, while in all columns except 1, standard errors increase monotonically, or very nearly so, with time from opening. That is, unsurprisingly, as the subway opening is more remote, its effects are progressively more difficult to detect, and beyond 5-6 years we are unable to distinguish subway effects from zero.

While these results support a subway effect on AOD of about 0.02 out to 5-6 years post-opening, beyond this we lose the ability to discriminate between hypotheses. On the one hand, the results seem consistent with a persistent AOD decrease of about 0.02 that is gradually overwhelmed by noise. On the other hand, we cannot distinguish effects beyond 6 or 7 years from zero.

B *Spatial scale of effect*

Subways overwhelmingly serve the areas close to the most central part of a city. Gonzalez-Navarro and Turner (2016) document that about 40% of all subway stations in existing subway systems lie within 5km of the center and another 30% within 10km of the center. Thus, we expect larger effects on AOD nearer to city centers than further away. Table 7 documents precisely this phenomena. For reference, the first two columns of this table reproduce the first two columns of table 4. Columns 3 and 4 are identical to columns 1 and 2, except that the dependent variable is mean monthly AOD within 25km of the center rather than within 10km. Columns 5 and 6 are similar, but examine AOD within 50km of the center. As expected, as we increase the distance from the center, we see

[12]In table 1 these 26 cities range from Rennes to Dubai.

Table 5: Longer term effects

	(1)	(2)	(3)	(4)	(5)	(6)
1-12 months post	-0.0203*	-0.0209*	-0.0186*	-0.0187*	-0.0222*	-0.0216*
	(0.0102)	(0.0104)	(0.0108)	(0.0109)	(0.0116)	(0.0113)
13-24 months post	-0.0127	-0.0132	-0.0178**	-0.0178*	-0.0250***	-0.0237**
	(0.00967)	(0.0101)	(0.00866)	(0.00927)	(0.00891)	(0.00899)
25-36 months post			-0.0271**	-0.0268**	-0.0366***	-0.0344***
			(0.0103)	(0.0101)	(0.0107)	(0.0100)
37-48 months post					-0.0316*	-0.0282**
					(0.0158)	(0.0135)
City pop. and country gdp	No	Yes	No	Yes	No	Yes
Mean dep. var.	0.462	0.462	0.443	0.443	0.416	0.416
R-squared	0.833	0.834	0.831	0.832	0.829	0.829
Number of events	38	38	35	35	28	28
N	11,841	11,841	10,881	10,881	8,863	8,863

*Note: Dependent variable is monthly mean AOD in a 10km disk centered around the city center for a constant sample of cities. Standard errors clustered at the city level in parentheses. All regressions include the following controls; linear and quadratic climate controls (temperature, vapor, cloud cover, precipitation, frost days), AOD pixel count, satellite indicator, calendar month × city indicators, year × continent indicators, pre- and post-period indicators. Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.*

decreases in the effect of subways on AOD. However, the effect continues to be distinguishable from zero at ordinary confidence levels, and the rate of decrease with distance is small compared to the precision of the estimates. In all, table 7 suggests that subways have greater effects on central city than suburban AOD.

C *Further results*

Placebo test: Table A.2 presents the results of an important placebo test. To conduct this test, we match each subway city to the nearest city within 1000km that has a population within 20% of the target city. We are able to find such a match for 27 of our 39 subway cities. We replicate the regressions of table 4 using placebo city outcomes in table A.2. As expected, the effect of subways on placebo city AOD is a precisely estimated zero.

Heterogenous effects: Table A.3 investigates whether subways have different effects on different types of cities. In this table, we replicate the results of column 2 of table 4, but add an interaction between the post-subway indicator and a particular city characteristic, along with the characteristic in question. In order, the interactions considered are; an indicator for cities in Asia, an indicator for cities in the top half of the city size distribution in 2000, an indicator for cities in the bottom half of the income distribution in 1990, an indicator for above median average rainfall, and finally,

Table 6: Even longer horizon

	(1)	(2)	(3)	(4)	(5)
1-12 months post	-0.0183	-0.0201*	-0.0201*	-0.0195*	-0.0196*
	(0.0113)	(0.0101)	(0.0101)	(0.00996)	(0.00978)
13-24 months post	-0.0238**	-0.0123	-0.0123	-0.0112	-0.0114
	(0.0103)	(0.00977)	(0.0100)	(0.0100)	(0.0100)
25-36 months post	-0.0320***	-0.0198*	-0.0197*	-0.0182*	-0.0185
	(0.00940)	(0.0102)	(0.0106)	(0.0106)	(0.0110)
37-48 months post	-0.0284*	-0.0185	-0.0185	-0.0167	-0.0170
	(0.0145)	(0.0140)	(0.0145)	(0.0144)	(0.0148)
49-60 months post	-0.0483***	-0.0380***	-0.0379**	-0.0357**	-0.0361**
	(0.0155)	(0.0137)	(0.0142)	(0.0142)	(0.0147)
61-72 months post			-0.0250*	-0.0228	-0.0233
			(0.0136)	(0.0144)	(0.0154)
73-84 months post				-0.0295	-0.0300
				(0.0179)	(0.0185)
85-96 months post					-0.0165
					(0.0210)
Constant sample of cities	Yes	No	No	No	No
City pop. and country gdp	Yes	Yes	Yes	Yes	Yes
Mean dep. var.	0.392	0.457	0.457	0.457	0.457
R-squared	0.833	0.834	0.834	0.834	0.834
Number of events	26	39	39	39	39
N	8,312	12,169	12,169	12,169	12,169

*Note: Dependent variable is monthly mean AOD in a 10km disk centered around the city center for a constant sample of cities. Standard errors clustered at the city level in parentheses. All regressions include the following controls; linear and quadratic climate controls (temperature, vapor, cloud cover, precipitation, frost days), AOD pixel count, satellite indicator, calendar month $\times$ city indicators, year $\times$ continent indicators, pre- and post-period indicators. Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.*

an indicator for cities whose subway opening included more than the median number of stations. Broadly, including the interaction term has a small effect on the magnitude or significance of the main treatment effect and the interaction term is always absolutely small and indistinguishable from zero. Thus, to the extent that subways affect different classes of cities in different ways, this effect is either too small to measure in our data or requires that we differentiate cities in some way that we do not consider.

These findings are of intrinsic interest. We know little about travel behavior in developing world cities, and the fact that we see similar responses to subways in developed and developing world cities suggests that in at least this regard, the two classes of cities are the same.

Table 7: Spatial decay

	10 km radius		25 km radius		50 km radius	
1-18 months post	-0.0205**	-0.0211**	-0.0187**	-0.0193**	-0.0135*	-0.0141*
	(0.00931)	(0.00957)	(0.00693)	(0.00721)	(0.00737)	(0.00771)
City pop. and country gdp	No	Yes	No	Yes	No	Yes
Mean dep. var.	0.457	0.457	0.412	0.412	0.377	0.377
R-squared	0.833	0.834	0.861	0.861	0.863	0.864
Number of events	39	39	39	39	39	39
N	12,169	12,169	12,535	12,535	12,644	12,644

*Note: Dependent variable is monthly mean AOD in a 10km, 25km, or 50km disk centered around the city center for a constant sample of cities. Standard errors clustered at the city level in parentheses. All regressions include the following controls; linear and quadratic climate controls (temperature, vapor, cloud cover, precipitation, frost days), AOD pixel count, satellite indicator, calendar month $\times$ city indicators, year $\times$ continent indicators, pre- and post-period indicators. Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.*

Expansions vs openings: Up until now, our investigations have focussed on the effects of the initial opening of a subway. We now turn to an investigation of subsequent expansions. To consider the effect of a city's first subway expansion (typically the second subway line in the system), as opposed to the system opening, we first restrict attention to the set of 14 cities for which we observe AOD for both the opening and the expansion. Column 3 of table A.4 reports the results of a regression like the one reported in column 2 of table 4 to estimate the effect on AOD of a city's first subway expansion over an 18 month treatment window. The point estimate of this effect is -0.019, about the same as the expansion effect from table 4 but we cannot distinguish this effect from zero.

Because we observe the whole history of each subway system, we can also identify the date of the first expansion for cities that do not open their subways during the period when we observe AOD. This increases the number of available expansions from 14 to 26. Column 1 of table A.4 reports the estimate of the expansion effect on this larger set of cities. This estimate is smaller and more precisely estimated, and while we cannot distinguish it from zero, we also cannot distinguish it from -0.02. Columns 2 and 4 replicate the estimations of columns 1 and 3, but use any expansion as the treatment variable. These estimates are both close to zero and estimated with sufficient precision to allow us to distinguish them from -0.02, but not from zero. In sum, this table provides suggestive evidence that subway expansions are less important than openings. Table A.5 examines the effects of subway openings and expansions of subway ridership and confirms the conclusions suggested by table A.4. An average subway opening results in ridership of about 65 people per 1000 of population. The first expansion, on average, increases ridership by about 47 people per 1000 of population, and subsequent expansions have still smaller effects.

Implications of longer pre-treatment period: The results of presented so far are consistent with subway openings causing a decrease in AOD of about 0.02, and with this effect being about constant over at least the subsequent 5 to 7 years. If we instead consider a pre-period of around 48 months, then there are two noteworthy changes. First, from table 1 the set of cities for which we observe a 48 month pre and post-period begins with Gwanngju, South Korea and ends with Shenyang, China, so we are left with a dramatically smaller sample. Second, there are three extremely low pollution months about 24 months prior to subway opening. The three months do not appear to indicate a break in either the trend or the level of AOD. However, they are sufficiently different from neighboring months that they shift the 48 month pre-period AOD mean. With this said, in regressions analogous to those of table 4 with the longer pre and post-treatment period and smaller sample, we estimate a decline in AOD around the time of subway opening which is only slightly smaller than what we report in table 4. Figure 8 illustrates this longer study period but is otherwise analogous to the bottom panel of figure 5.

6. The health value of subway induced AOD reductions

Arceo, Hanna, and Oliva (2016) use data describing Mexico city between 1997 and 2006 to estimate a weekly infant death rate of 0.24 per 100,000 per μg/m^3 of PM10. Thus, of 100,000 births, a 1 μg/m^3 decrease in ambient PM10 avoids about 12.5 infant deaths.[13] Knittel, Miller, and Sanders (2016) use data from California between 2002 and 2007 to estimate a weekly infant death rate of 0.19 per 1000 per μg/m^3 of PM10. This estimate implies that of 100,000 births, a 1 μg/m^3 decrease in ambient PM10 avoids about 9.9 infant deaths. Chay and Greenstone (2003) consider data describing infant deaths in about 1000 US counties between 1978 and 1984 and estimate that a one unit μg/m^3 decrease in ambient TSP avoids about 5.2 infant deaths per 100,000 births. Converting from TSP to PM10 is non-trivial, however PM10$= 0.55\times$TSP is a commonly used rule of thumb (World Bank Group and United Nations Industrial Development Organization, 1999). Rescaling the Chay and Greenstone estimate implies that a one μg/m^3 decrease in ambient PM10 avoids about 9.5 infant deaths per 100,000 births. In sum, these studies suggest that a one μg/m^3 decline in PM10 avoids about 10 infant deaths per 100,000 births.[14] That none of these estimates can be distinguished from the others despite a range of mean PM10 of from about 28 μg/m^3 for Knittel *et al.* (2016) to about 67 μg/m^3 for Arceo *et al.* (2016) suggests that the infant mortality response is approximately linear in PM10 (as Arceo *et al.* (2016) observe).

[13] An infant survives its first year if it survives 52 weeks. Thus a weekly death rate of 0.24×10^{-5} gives $[1-(1-(0.24\times 10^{-5}))^{52}]10^5 = 12.47$ infant deaths per 100,000 births.

[14] Currie and Neidell (2005) use data describing PM10 and infant mortality in California between 1989 and 2000 and conclude that PM10 has no measurable effect on infant mortality. Knittel *et al.* (2016) and Arceo *et al.* (2016) both replicate the Currie and Neidell (2005) research design and find much smaller effects than the IV estimates reported above. We note that Jayachandran (2009) and Gutierrez (2010) also estimate the effects of particulates on infant mortality. We do not discuss their estimates because they do not present their results in a way that permits a conversion to mortality rates per μg/m^3 of PM10.

An average city in our sample has a population of about 3.7 million in the year after its subway opens. With a 2% birthrate, 74,000 babies are born in such a city each year.[15] Subway openings cause about a 0.02 unit decrease in AOD. Using column 3 of table 3 to convert from AOD to PM10, this is about 1.2 μg/m^3 of PM10. At 10 infant deaths per 100,000 births per μg/m^3 of PM10, this means that in a city of average size, a subway opening averts about 8.9 infant deaths per year.

Using 6m as the value of a statistical life, this means that in an average city of 3.7m, the value of averted infant mortality is about 53m dollars per year. Our estimates do not allow us to conclude that subways continue to affect air quality beyond 5-6 years after their opening date. With a 5% discount rate, the discount present value of this amount over five years is about 240m dollars. If the effect is permanent, the corresponding present value is 1.06b dollars.

From figure 1 an average subway system carries about 60 riders per 1000 of population after its first few years of operation. In a sample average city of 3.7 million, this means that the subway system carries about 83 million riders per year. Dividing, this suggests that the external social benefit per subway rider due to reduced infant mortality is about 64 cents per rider.

These calculations are obviously crude. They do not account for mortality on other parts of the age distribution and do not account for morbidity at all. They do not account for possible effects on labor productivity, nor for the fact that subways may reduce pollutants other than PM10. While the magnitudes of these effects remain uncertain, they are surely positive, and possibly large, e.g., Chang, Zivin, Gross, and Neidell (2016) or Murray (2016). Thus, we might reasonably expect that a complete accounting for the health and productivity related benefits of subway induced improvements in air quality would lead to a much larger value than we describe above. On the other hand, 6m dollars per statistical life is high for a developing country, and reducing this value reduces our estimate proportionately.

Reporting on a sample of 138 subway systems in operation as of 2010, Gonzalez-Navarro and Turner (2016) report a mean system length of about 77km. Baum-Snow and Kahn (2005) examine 16 US subway systems and estimate constructions costs ranging between 25m and 287m dollars per mile. Using this range of cost estimates, the cost of construction for an average subway system ranges from 1.9b to about 22b dollars.

Our estimates of the present value of avoided infant mortality in an average subway city range between 240m and 1.06b, depending on whether the subway effect on pollution lasts for five years or is permanent. Comparing these magnitudes suggests that the value of subway induced improvements to air quality may be a non-trivial fraction of subway construction costs. Thus, our results seem to suggest that, absent a regulatory mechanism for managing automobile related pollution directly, air quality improvements probably justify a modest subsidy of subway construction or ridership.

[15]The World Bank reports that the world average crude birth rate is 19.5/1000 (`http://data.worldbank.org/indicator/SP.DYN.CBRT.IN`, accessed April 2017).

In light of the results in table A.4, these subsidies are probably justified only for subway openings, not fot subsequent expansions.

7. Subways, AOD and urban travel behavior

To assess whether our estimate of the effect of subway openings on AOD is reasonable, consider the following back of the envelope calculations.

On the basis of travel survey data described in Akbar and Duranton (2017), residents of Bogota take about 2.69 trips per day, and of these 19.3%, or 0.52 trips per day, are by private car or taxi. From table 1, twelve months after its subway opening an average city in our sample has a population of about 3.7m. Multiplying per capita trips by this population, if people drive at the same rate as does the population of Bogota then an average city in our sample generates about 2m trips by car or taxi per day. From figure 5, in the second year of its operation an average subway in our data provides about 60 rides per 1000 of population. Applying this rate to a city of 3.7m, an average subway system provides about 200,000 rides per day. If all subway rides replace car or taxi rides, this is about 10% of all rides in our hypothetical city.

We can perform a similar calculation on the basis of US national averages using the 2009 National Household Transportation Survey.[16] The 2009 NHTS records that an average US household took 3.8 trips per day, about 90% by car (Duranton and Turner, 2017). If everyone in a city of 3.7m takes as many trips as an average American, then the city generates about 13m trips by car per day. If the subway system provides the same about 200,000 rides per day and if all subway rides replace car or taxi rides, then the subway opening should reduce car trips by about 1.5%.

Suppose a 1% reduction in traffic results in a 1% reduction in PM10 and that there is no demand response for car travel as drivers shift trips to the subway. In this case, the calculations above show that a subway reduces PM10 by 10% in a city like Bogota and by 1.5% the US. These values bracket our sample average 5% AOD reduction. Since our estimated 5% AOD reduction is an average over rich and poor country cities, this suggests that our estimated effects are plausible.

With this said, the evidence for a direct relationship between driving and metropolitan PM10 levels is inconclusive. Friedman, Powell, Hutwagner, Graham, and Teague (2001) examine changes in traffic and changes in PM10 in Atlanta around the 1996 summer olympics. During this time, the city imposed restrictions on driving and saw traffic fall by about 2.8% over a 17 day period. During the same period, PM10 fell by 16.1%. That is, each 1% reduction in driving was associated with about a 3% reduction in PM10. In a related exercise, Gibson and Carnovale (2015) examine the effect of a change in Milan's congestion pricing program on both traffic and PM10. Their estimates allow us to calculate that a 16% reduction in traffic caused about a 4% reduction in

[16] nhts.ornl.gov/2009/pub/stt.pdf, table 3.

PM10.[17] Finally, the US EPA attributes about 16% of US PM10 to on road vehicles. [18] Of these studies, only Friedman *et al.* (2001) finds that a one percent decrease in traffic is associated with at least a one percent decrease in PM10. The weight of evidence suggests a smaller response.

This has important implications for our back of the envelope calculations. Suppose that, in line with Gibson and Carnovale (2015), we require 4% reduction in traffic for each 1% decrease in PM10. In this case, in order to achieve a 5% reduction in PM10, a subway opening would need to reduce traffic by 20%, not by 5%. This seems implausible. Alternatively, if subway openings reduce driving by 5% then we would expect them to reduce PM10 by 1.25%.

In addition, the evidence that drivers respond to increased road capacity seems compelling. Duranton and Turner (2011) find that metropolitan area traffic increases in direct proportion to road capacity, a finding that Hsu and Zhang (2014) confirm for Japan. While these papers study road expansions explicitly, the logic of their finding suggests that a reduction in traffic due to increased subway ridership ought to be met with almost exactly offsetting increases in the demand for automobile and truck travel. That is, that subways ought not to reduce traffic in urban areas. Duranton and Turner (2011) corroborate this argument by looking at the relationship between the level of driving in a US metropolitan area and the stock of buses and subway cars in the MSA. Although the resulting estimates are imprecise, they do not contradict the hypothesis of no effect.

Duranton and Turner (2011) and Hsu and Zhang (2014) study, respectively, US and Japanese metropolitan areas with average populations of about 1m. In contrast, we consider a set of cities with average population of nearly 4m, of which only one is Japanese and only two are in the continental US. Thus, it may be that the demand responses estimated in Duranton and Turner (2011) and Hsu and Zhang (2014) do not extrapolate to our sample of larger and more international cities. With this said, the hypothesis of no demand response seems improbable.

This, too, has important implications for our back of the envelope calculation. Suppose that the demand response in our sample is only half what Duranton and Turner (2011) find for the US. In this case, in order to reduce driving by one trip, we would require two subway trips. This would halve the effect of subways PM10 in our back of the envelope calculation.

To sum up, subway openings reduce metropolitan AOD levels by about 5% and probably carry approximately the same fraction of daily trips. However, the weight of evidence suggest a significant traffic demand response following a subway opening and that a 1% traffic reduction will lead to a reduction of PM10 that is probably less than 1%. It follows that the effect of subways on AOD probably does not operate entirely by diverting travel from cars to the subway. Subway openings probably must have a larger effect on driving behavior than ridership numbers alone suggest to cause the observed decrease in PM10.

[17]From Gibson and Carnovale (2015) table 6, treatment increased log PM10 by 0.0404 and, from table 2, traffic by 26,725 cars. From table 2, mean traffic and PM10 are 169,744 and 47.66. Using these values to calculate percentage changes we arrive at a 16% change in traffic and 4% change in PM10.

[18]U.S. EPA, Report on the Environment, [19], accessed, April 2017.

We are not able to resolve this puzzle beyond suggesting three alternative channels through which subways might affect PM10. First, marginal drivers who switch to the subway may be poor relative to the pool of all drivers, and if so, they may drive particularly dirty cars. Thus, the availability of subways may affect pollution by affecting the composition of the stock of cars on the road. There does not seem to be a basis in the literature for estimating the magnitude of this effect. Second, subways typically provide a disproportionate share of their trips at peak hours. In this case, subway trips may replace trips that occur at particularly congested times. Or, put another way, subway trips may replace car trips that have particularly high external congestion costs. If so, it may be that each subway rider has a disproportionate effect on pollution because they reduce pollution produced by other commuters. Anderson (2014) provides evidence, over the very short run, to support this idea. Third, subways may sometimes require the conversion of space previously dedicated to roads to subway rail. In this case, subways might result in much larger reductions in traffic by directly reducing the capacity of the road network. Resolving these issues is a subject for future research and will likely have important implications for the welfare evaluation of subway construction.

8. Conclusion

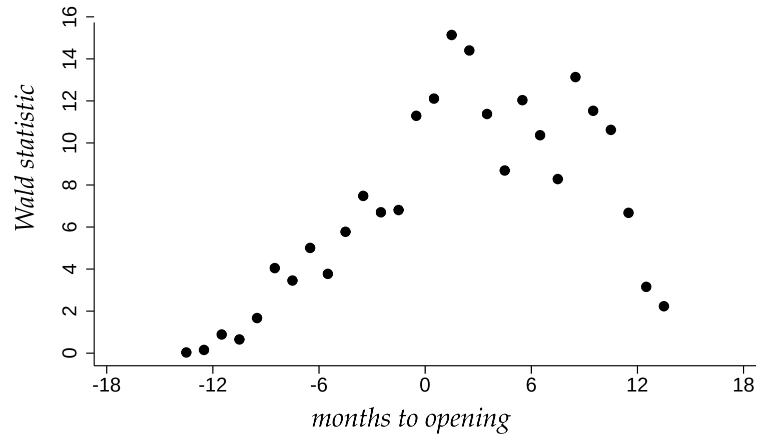
Column 2 of table 4 indicates that AOD fell by about 0.021 in the 10k disk surrounding a city center during the 18 months following an average subway opening. This effect is robust to econometric specification, and is estimated precisely, the 95% CI is [-0.040,-0.002]. Mean monthly AOD in the regression sample is about 0.46. Dividing, the mean AOD reduction from a subway opening is about 5% with a 95% confidence interval ranging from 0.5% to not quite 10%. From table 2, AOD readings from Terra in 2000 and 2014 are 0.38 and 0.45. Our 0.02 estimated subway effect is only about 5% of the level of AOD, but it is more than 25% of the 14 year change. Comparing across continents in 2014, we see that the difference between Europe and North America is about 0.07, three and a half subway effects, and between Europe and Asia the difference is 0.38, about 20 subway effects. In all, this suggests that subways may play an economically important role in determining the growth of AOD in a city, but that other factors are important for determining the level.

To the extent that our data allows us to consider longer post-opening periods, this effect of subways on AOD appears to be approximately constant during the 5-6 years after an opening, and indeterminant beyond this time. As we consider larger areas around the city center, the effects of subway openings attenuate in intuitive ways. From table 7, AOD fell by about 0.019 in the 25k disk surrounding a city center during the 18 months following and average subway opening, just less than the effect in the 10km disk. For a 50k disk the corresponding point estimate of 0.014 is consistent with about a 3% drop.

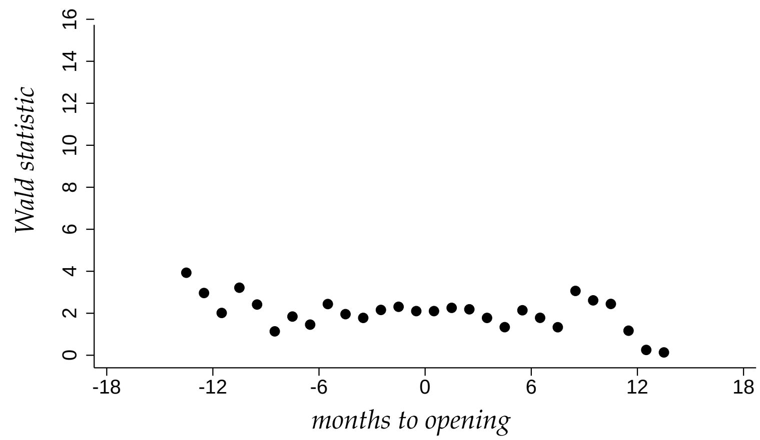
The effects of subway expansions seem to be dramatically smaller than those of subway openings, an effect we that observe both in changes in AOD and ridership. To the extent that public policy encourages subway construction, this suggests that openings are relatively more important than expansions. We note that the decreasing marginal effect of subway expansion seem to broadly consistent with the slight decreasing returns in the effects of metropolitan road networks observed in Couture, Duranton, and Turner (2016).

Extant estimates of the effects of PM10 on infant mortality suggest that PM10 is sufficiently poisonous that the small nominal reductions from subway openings are economically important. In particular, they appear to be large enough to justify moderate subsidies for subway construction in environments where more direct policy instruments for managing automobile pollution are not available. On the other hand, the channel through which subways affect pollution remains somewhat uncertain. Our calculation suggest that observed levels of ridership account for a significant fraction of metropolitan travel, but are unlikely to be large enough to cause the observed reduction ion AOD. Understanding the channels through which subways serve to reduce pollution remains a topic for future research.

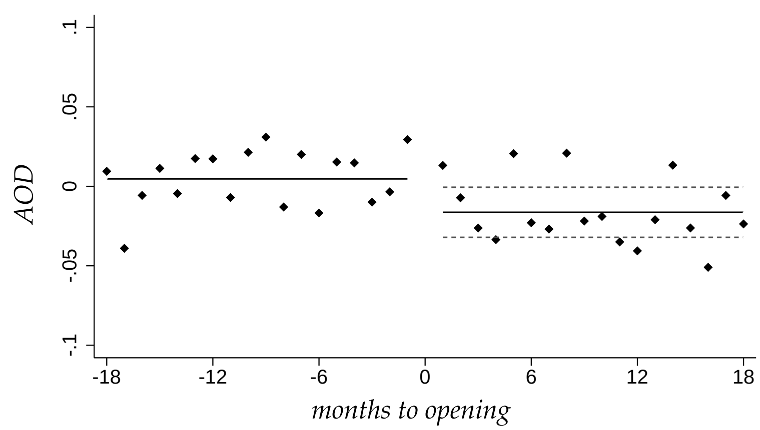
Figure 5: AOD during the 18 months before and after subway openings



(a) Test for discontinuity



(b) Test for trend break



(c) Event study

Notes: (a) Plot of Wald statistics for tests of a regression intercept discontinuity at time τ. Test statistics calculated in regressions that also control for a satellite indicator, year-by-continent indicator variables, city-by-calendar month indicators, AOD pixel-days and linear and quadratic terms of monthly of climate variables. Finally, the control set also includes linear and quadratic terms in country level GDP and city level population. (b) Plot of Wald statistics for tests of a trend break at time τ conditional on a discontinuity in the mean level of AOD at $\tau = 1$. Other details are the same as in Panel (a). (c) Event study during 18 months before and after subway openings.

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Appendix: Supplemental results

Table A.1: Subway opening and AOD by 6 month period, pre- and post-system opening

	(1)	(2)	(3)	(4)	(5)	(6)
1-6 months post	-0.0134	-0.0141	-0.0139	-0.0144	-0.0144	-0.0147
	(0.0134)	(0.0137)	(0.0135)	(0.0137)	(0.0130)	(0.0132)
1-12 months post	-0.0249*	-0.0252*	-0.0250*	-0.0253*	-0.0232*	-0.0238*
	(0.0137)	(0.0138)	(0.0135)	(0.0134)	(0.0127)	(0.0129)
13-18 months post	-0.0226	-0.0230	-0.0225	-0.0228	-0.0189	-0.0198
	(0.0157)	(0.0162)	(0.0159)	(0.0160)	(0.0155)	(0.0160)
7-12 months pre	0.00668	0.00652	0.00569	0.00615	0.00892	0.00926
	(0.0120)	(0.0121)	(0.0122)	(0.0121)	(0.0127)	(0.0127)
13-18 months pre	-0.00711	-0.00654	-0.00793	-0.00707	-0.00140	-0.000921
	(0.0113)	(0.0112)	(0.0113)	(0.0112)	(0.0118)	(0.0120)
city pop.& GDP	No	Yes	No	Yes	No	Yes
city-level trends	No	No	Yes	Yes	No	No
city-level pre/post trends	No	No	No	No	Yes	Yes
Mean dep. var.	0.457	0.457	0.457	0.457	0.457	0.457
R-squared	0.833	0.834	0.838	0.838	0.839	0.839
Number of events	39	39	39	39	39	39
N	12,169	12,169	12,169	12,169	12,169	12,169

*Note: Dependent variable is monthly mean AOD in a 10km disk centered around the city center for a constant sample of cities. Standard errors clustered at the city level in parentheses. All regressions include the following controls; linear and quadratic climate controls (temperature, vapor, cloud cover, precipitation, frost days), AOD pixel count, satellite indicator, calendar month $\times$ city indicators, year $\times$ continent indicators, pre- and post-period indicators. Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.*

Table A.2: Placebo city AOD for 18 month period post system opening

	(1)	(2)	(3)	(4)	(5)	(6)
1-18 months post	0.00484	0.00574	0.00402	0.00562	-0.00393	-0.00118
	(0.0103)	(0.0111)	(0.00951)	(0.0102)	(0.00882)	(0.00919)
city pop.& GDP	No	Yes	No	Yes	No	Yes
city-level trends	No	No	Yes	Yes	No	No
city-level pre/post trends	No	No	No	No	Yes	Yes
Mean dep. var.	0.436	0.440	0.436	0.440	0.436	0.440
R-squared	0.817	0.819	0.822	0.822	0.823	0.824
Number of events	27	25	27	25	27	25
N	8,105	7,528	8,105	7,528	8,105	7,528

*Note: Dependent variable is monthly mean AOD in a 10km disk centered around the city center. Standard errors clustered at the city level in parentheses. All regressions include the following controls; linear and quadratic climate controls (temperature, vapor, cloud cover, precipitation, frost days), AOD pixel count, satellite indicator, calendar month $\times$ city indicators, year $\times$ continent indicators, pre- and post-period indicators. Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.*

Table A.3: Heterogenous effects

	(1)	(2)	(3)	(4)	(5)
	Asia	Big City	Poor	Rainy	Big Subway
1-18 months post	-0.0150*	-0.0226**	-0.0218**	-0.0205*	-0.0204**
	(0.00791)	(0.00988)	(0.00868)	(0.0103)	(0.00953)
Interaction	-0.0103	0.00327	0.00150	-0.00124	-0.00146
	(0.0116)	(0.0143)	(0.0125)	(0.0139)	(0.0139)
Mean dep. var.	0.457	0.457	0.457	0.457	0.457
R-squared	0.834	0.834	0.834	0.834	0.834
Number of events	39	39	39	39	39
N	12,169	12,169	12,169	12,169	12,169

*Note: Dependent variable is monthly mean AOD in a 10km disk centered around the city center for a constant sample of cities. Standard errors clustered at the city level in parentheses. All regressions include the following controls; linear and quadratic climate controls (temperature, vapor, cloud cover, precipitation, frost days), AOD pixel count, satellite indicator, calendar month $\times$ city indicators, year $\times$ continent indicators, pre- and post-period indicators, city population and country GDP. Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.*

Table A.4: Expansions

	All Cities		Main Cities	
	(1)	(2)	(3)	(4))
Expansions	*2^{nd}*	$\geq$*2^{nd}*	*2^{nd}*	$\geq$*2^{nd}*
1-18 months post	-0.0115	-0.00152	-0.0193	-0.00273
	(0.00854)	(0.00329)	(0.0153)	(0.00952)
Mean dep. var.	0.516	0.488	0.613	0.633
R-squared	0.817	0.816	0.777	0.806
Number of events	26	104	14	21
N	8,110	31,323	4,375	6,678

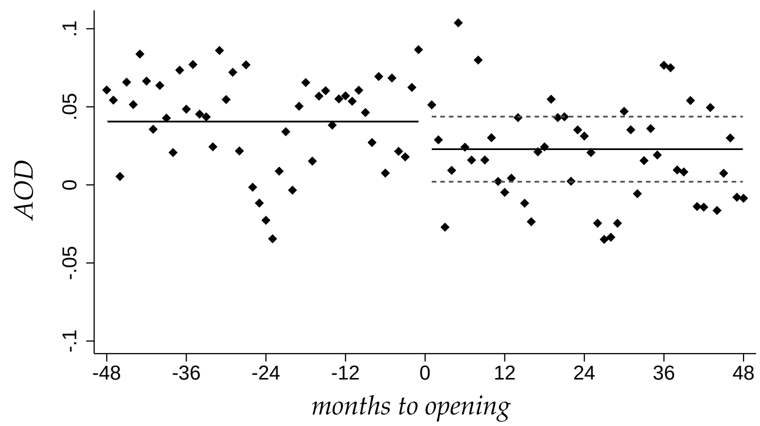
*Note: Dependent variable is monthly mean AOD in a 10km disk centered around the city center. Standard errors clustered at the city level in parentheses. All regressions include the following controls; linear and quadratic climate controls (temperature, vapor, cloud cover, precipitation, frost days), AOD pixel count, satellite indicator, calendar month $\times$ city indicators, year $\times$ continent indicators, pre- and post-period indicators. Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.*

Table A.5: Results on ridership per capita

	(1)	(2)	(3)
Event	*1^{st}*	*2^{nd}*	$\geq$*2^{nd}*
1-18 months post	64.51*	46.67***	30.09*
	(34.15)	(7.581)	(13.87)
Mean dep. var.	35.91	40.87	41.86
R-squared	0.505	0.946	0.938
Number of events	28	8	15
N	8271	2228	3685

*Note: Dependent variable is ridership per 1000 of population. Standard errors clustered at the city level in parentheses. All regressions include the following controls; linear and quadratic climate controls (temperature, vapor, cloud cover, precipitation, frost days), AOD pixel count, satellite indicator, calendar month $\times$ city indicators, year $\times$ continent indicators, pre- and post-period indicators. Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.*

Figure A.1: AOD during the 48 months before and after subway openings



(c) Event study

Notes: Event study during 48 months before and after subway openings, constant sample of 21 cities.

Appendix: Data

Ridership

We gathered subway ridership data (unlinked trips) for 30 of the subway systems in our sample, mostly from annual reports or statistical agencies. In 13 cases we were either not able to find data on ridership at all, the data were not available from the opening date, or the ridership data was aggregated across cities or other rail systems. Data sources for each of the cities we were able to obtain usable data are detailed in Table 1. For ten of the cities we were able to obtain data, ridership was reported at the monthly level. For the other 20, quarterly or yearly data was available and we used linear interpolation to create a monthly level ridership dataset.

AOD

The Moderate Resolution Imaging Spectroradiometers (MODIS) aboard the Terra and Aqua Earth observing satellites measure the ambient aerosol optical depth (AOD) of the atmosphere almost globally. We use MODIS Level-2 daily AOD products from Terra for February 2000-December 2014 and Aqua for July 2002-December 2014 to construct monthly average AOD levels in cities.

We download all the files from the NASA File Transfer Protocol[20]. There are four MODIS Aerosol data product files: $MOD04\_L2$ and $MOD04\_3K$, containing data collected from the Terra platform; and $MYD04\_L2$ and $MYD04\_3K$, containing data collected from the Aqua platform. We use products $MOD04\_L2$ and $MYD04\_L2$ to get AOD measures at a spatial resolution (pixel size) of approximately 10 x 10 kilometers and products $MOD04\_3K$ and $MYD04\_3K$ to get AOD measures at a spatial resolution of approximately 3 x 3 kilometers.

Each product file covers a five-minute time interval based on the start time of each MODIS granule. The product files are stored in Hierarchical Data Format (HDF) and we use the "Optical Depth Land And Ocean" layer, which is stored as a Scientific Data Set (SDS) within the HDF file, as our measure of aerosol optical depth. The "Optical Depth Land And Ocean" dataset contains only the AOD retrievals of high quality.

We convert all HDF formatted granules to GIS compatible formats using the HDF-EOS To GeoTIFF Conversion Tool (HEG) provided by NASA's Earth Observing System Program[21].

We consolidate every GeoTIFF granules into a global raster for each day using ArcGIS. First, we keep only AOD values that do contain information. The missing value is -9999 in AOD retrievals. Second, we create a raster catalog with all the granules for a given day and calculate the average AOD value using the Raster Catalog to Raster Dataset tool.

Figure A.2 provides more information about the coverage of the two satellites and the prevalence of missing data. The black dashed line in panel (a) of figure gives the count of cities in our

[20] ftp://ladsweb.nascom.nasa.gov/allData/6/

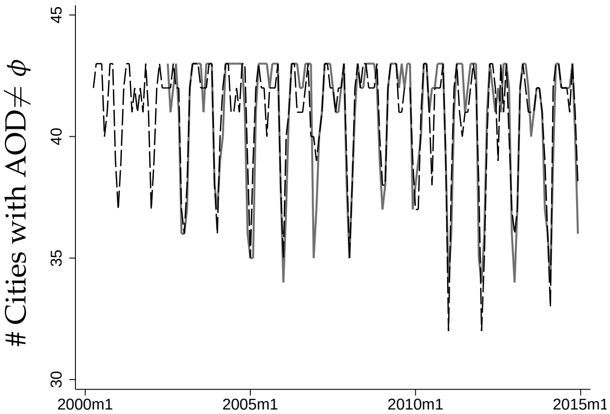
[21] The most recent version of the software, HEG Stand-alone v2.13, can be downloaded at http://newsroom.gsfc.nasa.gov/sdptoolkit/HEG/HEGDownload.html

Table A.6: Ridership data sources

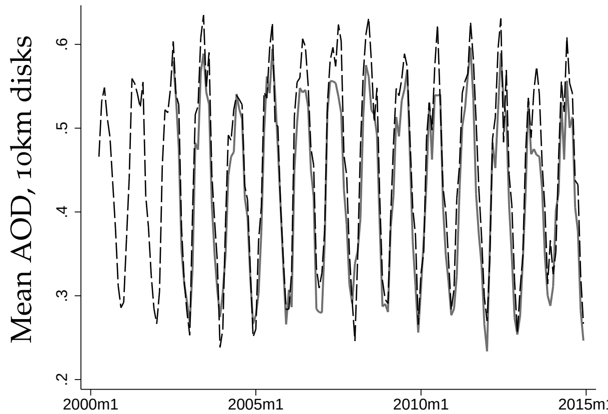
City	Source
Almaty (Kazakhstan)	International Metro Association Reports
Bangalore (India)	Bangalore Metro Operational Performance
Brescia (Italy)	Brescia Mobilitá Reports
Copenhagen (Denmark)	Statistics Denmark
Daejon (South Korea)	Daejon Metropolitan Rapid Transit Corporation
Delhi (India)	Delhi Metro Rail Corporation Annual Reports
Dubai (UAE)	Dubai Road and Transport Authority Annual Statistical Reports
Gwangju (South Korea)	Gwangju Subway Reports
Hangzhou (China)	Hangzhou Statistical Yearbook
Istanbul (Turkey)	Metro Istanbul Statistics (Only line M2)
Kazan (Russia)	International Metro Association Reports
Kaohsiung (Taiwan)	Kaohsiung Rapid Transit Corp. Transport Volume Statistics
Las Vegas (USA)	NTA National Transit Database and Webarchive lvmonorail
Lausanne (Switzerland)	Transports Lausanne Annual Reports
Lima (Peru)	Ministerio de Transportes y Comunicaciones Perú
Mashhad (Iran)	Mashhad Urban Railway Operation Company Planning and Development
Naha (Japan)	Japan Ministry of Land, Infrastructure, Transport and Tourism
Palma (Spain)	Instituto Nacional de Estadística España
Porto (Portugal)	Statistics Portugal, Light Rail (Metro) Survey
San Juan Puerto Rico (USA)	Instituto de Estadísticas de Puerto Rico
Santo Domingo (DR)	Oficina para el Reordenamiento del Transporte
Seattle (USA)	Sound Transit (Only Central Link Line) Performance Reports
Seville (Spain)	Instituto Nacional de Estadística España
Shenzhen (China)	Shenzhen Municipal Transportation Commission
Shenyang (China)	Shenyang Statistical Information Net
Suzhou, Jiangsu (China)	Suzhou Statistical Yearbook
Tehran (Iran)	Tehran Metro Research and Development
Turin (Italy)	Gruppo Torinese Transporti Reports
Valparaiso (Chile)	Memoria Anual Metro Valparaiso
Xian, Shaanxi (China)	Xian Bureau of Statistics

We were not able to obtain ridership data from the time of opening for the following 13 cities in the sample: Algiers (Algeria), Brasilia (Brazil), Bursa (Turkey), Chengdu (China), Chongqing (China), Dalian (China), Izmir (Turkey), Kunming (China), Maracaibo (Venezuela), Nanjing (China), Rennes (France), Valencia (Venezuela), and Wuhan (China).

Figure A.2: MODIS Terra and Aqua AOD data



(a)



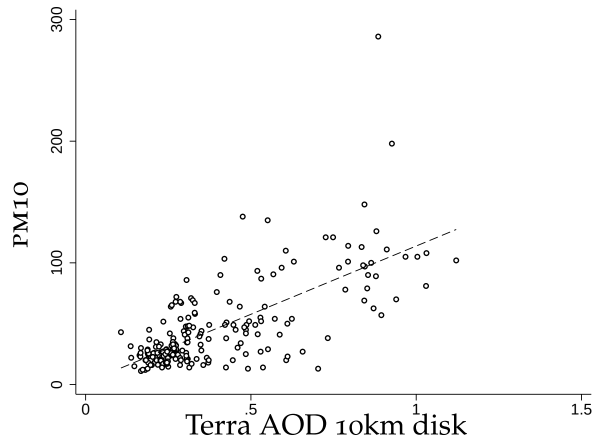
(b)

Panel (a) gives count of subway cities months with AOD 10km measurements by month for Terra (dashed black) and Aqua (gray). Panel (b) shows mean AOD within 10km of the center of subway cities, averaged over cities, by month for Terra (dashed black) and Aqua (gray).

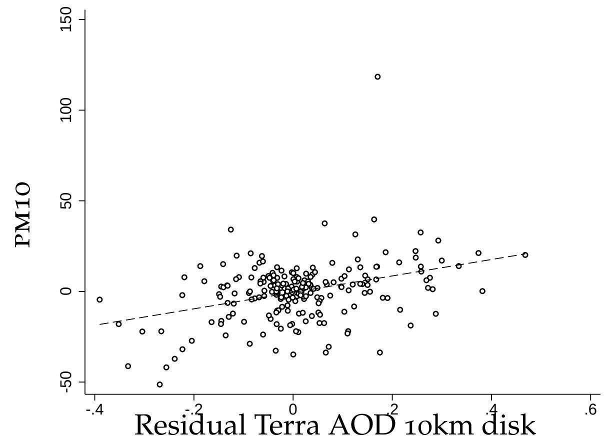
data for which we calculate an AOD from the Terra satellite reading for each month of our study period. These are cities for which there is at least one pixel within 10km of the center on one day during the relevant month. Since most of the cities in our data are in the Northern hemisphere, we see a strong seasonal pattern this series. The light gray line in this figure reports the corresponding quantity calculated from the Aqua satellite reading. Since Aqua became operational after Terra, the Aqua series begins later. The Aqua satellite data tracks the Terra data closely, but at a slightly lower level. Panel (b) of figure A.2 reports city mean AOD data for all city-months in our sample over the course of our study period. As for the other series, this one too exhibits seasonality, although this will partly reflect a composition effect. As we see in panel (a) not all cities are in the data for all months. As in the first two panels, the dark line describes AOD readings from Terra and the light gray, Aqua.

Finally, figure A.3 shows the relationship between the ground based measurements and MODIS AOD. Panel (a) of this figure plots ground based PM10 against Terra AOD in a 10km disk. That is, the raw data on which column 1 of table 3 is based. We see a strong positive relationship. Panel (b) shows a plot of the residuals of the regression in column 3 of table 3 against the residuals of a regression of 10km Terra PM10 on the control variables used in the same regression. Again, we see a strong positive slope. Note that the scales on the two graphs are not the same. The bottom two panels are the same as the top, but are based on ground based PM2.5 measures. Again we see a clear positive slope in both plots.

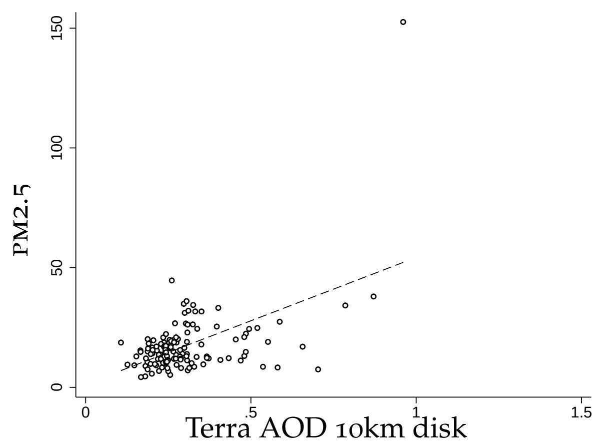
Figure A.3: Plots of ground-based PM10 and PM2.5 vs. MODIS AOD



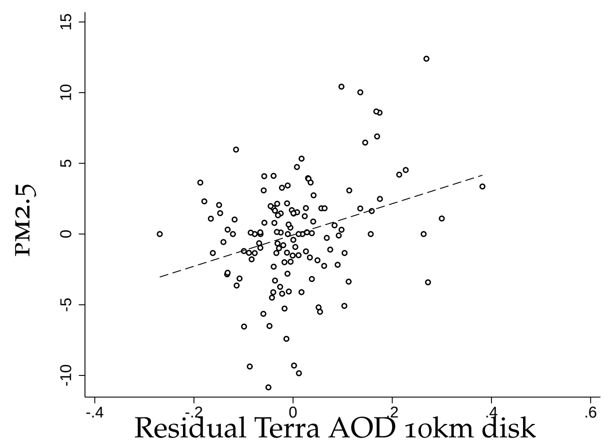
(a)



(b)



(c)



(d)

Note: Panel (a) Plot of ground-based PM10 against Terra MODIS AOD in a 10km disk. Panel (b) Plot of ground-based PM10 residual against Terra MODIS AOD in a 10km disk residual. Panel (c) Plot of ground-based PM2.5 against Terra MODIS AOD in a 10km disk. Panel (d) Plot of ground-based PM2.5 residual against Terra MODIS AOD in a 10km disk residual. NB: Scales not constant across graphs.