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Subways and Urban Growth: Evidence from Earth

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Abstract
We investigate the relationship between the extent of a city's subway network, its population and its spatial configuration. To accomplish this investigation, for the 632 largest cities in the world, we construct panel data describing the extent of each of the 138 subway systems in these cities, their population, and measures of centralization calculated from lights at night data. These data indicate that large cities are more likely to have subways, but that subways have an economically insignificant effect on urban population growth. Consistent with economic theory and with other studies of the effects of transportation improvements on cities, our data also indicate that subways cause cities to be more decentralized. For a subset of subway cities we also observe panel data describing subway and bus ridership. We find that a 10% increase in subway extent causes about a 6% increase in subway ridership and has no effect on bus ridership. Consistent with the available literature describing the effect of roads on cities, our results are consistent with subways having a larger effect on the configuration of cities than on their sizes, and with subways having a larger effect on discretionary than commute travel.

Keywords: subways, public transit, urban growth, urban decentralization
JEL Classifications: L91; R4; R11; R14

1. Introduction

We investigate the relationship between the extent of a city's subway network and its population, transit ridership and spatial configuration. To accomplish this investigation, for the 632 largest cities in the world, we construct panel data describing the extent of each of the 138 subway systems in these cities. We also assemble data describing their population and measures of centralization calculated from lights at night data. For a subset of the subway cities we also assemble panel data describing bus and subway ridership.

These data suggest the following three conclusions. First, while large cities are more likely to have subways, subways have a precisely estimated zero effect on urban population growth. Second, subways cause cities to decentralize. Third, a 10% increase in subway extent leads to about a 6% increase in subway ridership and does not affect bus ridership. Back of he envelope calculations suggest that most new subway riders are not commuters. All of these conclusions are broadly consistent with what is known about the effects of roads on urban development and travel behavior.

Our investigation is important for three reasons. First, understanding the effect of subways on cities is important if we are to evaluate proposals to build or extend subway systems. In 2010 the 632 cities in our dataset contained 138 subway systems consisting of 7,886 subway stations and about 10,700km of subway routes. Subway construction and expansion projects range from merely expensive to truly breathtaking. Among the 16 subway systems examined by Baum-Snow and Kahn (2005), construction costs range from about 25m to 550m USD2005 per km. On the basis of the mid-point of this range, 287m per km, construction costs for the current stock are about 3 trillion dollars.

These costs are high enough that subway projects generally require large subsidies. To justify these subsidies, proponents often assert the ability of a subway system to encourage employment growth. A statement by the agency responsible for Toronto's transit expansion is typical: "Expanding transportation can help create thousands of new green and well-paid jobs, and save billions of dollars in time, energy and other efficiencies."[1] An objective of the paper is to assess the validity of these claims.

There is little evidence that subways have such transformative effects. To date, there has been no city level statistical analysis of the effect of subway extent on any outcome other than ridership. If subways truly transform cities, as their proponents claim, then we should expect a migration of people into these cities. That our data do not provide evidence for such a migration suggests that the evaluation of prospective subway projects should rely less on the ability of subways to promote growth and more on the demand for mobility. Our data allows the first panel data estimates of the impact of changes in system extent on ridership and are therefore an important contribution to such evaluations.

[1] `http://www.metrolinx.com/en/regionalplanning/bigmove/big_move.aspx` (accessed July 28, 2014).

Understanding the effect of subways on cities is also important to policy makers interested in the process of urbanization in the developing world. Over the coming decades, we expect an enormous migration of rural population towards major urban areas. As a consequence, we can reasonably expect demands for urban infrastructure that are large relative to the ability of local and national governments to supply it. In order to assess trade-offs between different types of infrastructure in these cities, understanding the implications of each for welfare is clearly important. Since people move to more attractive places and away from less attractive ones (broadly defined), our investigation of the relationship between subways and population growth will help to inform these decisions. That subways have at most a tiny effect on population growth suggests that infrastructure spending plans in developing world cities should give serious consideration to non-subway infrastructure.

This paper speaks to three major research fields in urban economics. First, a large body of urban economic theory has posited that large cities are more productive (i.e. Fujita and Thisse, 2002). The results presented here dispel the notion that subway construction and operation subsidies can be justified by agglomeration effects. Second, the urban decentralization results shed light on the fundamental choice of work and firm location in a city — traditionally taken as given in transportation mode choice models (a literature pioneered by McFadden, 1973). Finally, there is a very active academic literature investigating the effect of transportation infrastructure on the growth and configuration of cities. In spite of their prominence in policy debates, subways have so far escaped the attention of this literature. This primarily reflects the relative rarity of subways. Most cities have roads so a single country can provide a large enough sample to analyze the effects of roads on cities. Subways are too rare for this. To conduct a statistical analysis of the effect of subways on cities requires data from, at least, several countries. An important contribution of this paper is to overcome this data problem by collecting data that describe all of the world's subway networks. In addition, with few exceptions, the current literature on the effects of infrastructure is static or considers panel data that is too short to investigate the dynamics of infrastructure's effects on cities. Because our panel spans the 60 year period from 1950 until 2010, we are able to investigate such dynamic responses to the provision of subways.

To estimate the causal effects of subways on urban growth and urban form, we must grapple with the fact that subway systems and stations are not constructed at random times and places. This suggests two potential threats to causal identification. The first results from confounding dynamics in the population growth process. This could occur if subway expansions systematically occur at times when the cities population growth is slower (or faster) than average. This might occur if construction crews leave the city when new subway expansions are complete or if subway expansions tend to occur when some other constraint to a city's growth begins to bind. The second results from omitted variables. If cities expand their bus networks in years when they do not expand their subway networks, and if bus and subway networks are substitutes, then any regression of population growth on subway growth that omits a measure of the bus network will be biased downward. We detail our strategy for dealing with both problems below. Briefly, we deal with the problem of confounding dynamics by exploiting the panel structure of our data and with the problem of omitted variables by experimenting with an exhaustive set of controls, but postpone a more detailed discussion of these strategies to section 5.

2. Literature

A *Subways*

With a few exceptions that we describe below, the literature that analyzes the effects of subways on cities consists entirely of analyses of a single city. Nevertheless, this literature is large and we here focus our attention on the small set of papers which attempt to resolve the problem of non-random assignment of subways. More complete surveys are available in Billings (2011) and Gibbons and Machin (2005).

Gibbons and Machin (2005) examine housing prices in London during the periods 1997-1999 and 2000-2001. These two year periods bracket two expansions of the London underground, six new stations and an extension of the Docklands light rail. Gibbons and Machin (2005) calculate various difference-in-differences estimates of the effect of these transit expansions on housing prices. They find that houses near a new transit station appreciate about 5% relative to houses further away, where a house within 2km is 'near' a subway station. Using a refinement of this estimator that allows distance to vary continuously, they find that moving one km away from a subway station decreases values by about 2% for the first two km, and about zero thereafter.

Billings (2011) conducts a similar exercise for a new light rail line in Charlotte, North Carolina. Charlotte opened a new light rail system in November 2007.[2] This system extended along one line, for about 15km, with 15 stations along the route. Like Gibbons and Machin (2005), Billings (2011) estimates the effect of subways on housing prices using a difference-in-differences estimator, where 'before' and 'after' refer to housing prices in the periods before and after the opening of the system. However, 'near' and 'far' are defined slightly differently. First, distance is defined as distance to the subway line rather than distance to a station. Given that stations are about 1km apart this is probably not important. Second, houses 'far' from the station are restricted to be close to alternate corridors that were candidates for a transit network that was ultimately not built, on the grounds that houses in alternate corridors are likely to resemble those in the successful corridor in unobserved ways. Despite the differences in milieu and method, Billings (2011) arrives at estimates quite close to those of Gibbons and Machin (2005): single family houses within 1.6km of the transit line see their prices increase by about 4% while condominiums see their prices rise by about 11%. Note that, like Gibbons and Machin (2005), Billings (2011) observes that changes result from subway construction over the course of just a few years.

[2] The Charlotte light rail system is not completely isolated from pedestrian and automobile traffic and so does not appear in our data as a subway.

Each of these papers makes a credible attempt to overcome the fact that subway systems are not located randomly within cities. However, neither provides us with much information about the relationship between subways and city-level growth. If subways affect the growth of cities, then they may affect it everywhere, both near and far from the station. Such citywide effects are, by construction, invisible to the differences-in-differences methodology.

Therefore, while the existing literature makes some progress on the problem of non-random assignment of subways to places, it does so at a high cost. The difference-in-differences methodology cannot tell us about the effect of changes in the overall level of activity within a city and, unless we are specifically interested in reorganizing economic activity across neighborhoods within a city, it is such changes in the overall level which are of primary policy interest and which are the object of our investigation.

Finally, in an important contribution Ahlfeldt, Redding, Sturm, and Wolf (2015) estimate a structural model of how a subway network can restructure a city, rather than just whether subways attract development. Given this, it is closest in spirit to our decentralization exercise. With this said, Ahlfeldt *et al.* (2015) use time series variation from just one city, so their ability to investigate the effect of subways on urban growth relies heavily the assumptions underlying their model.

The only studies (of which we are aware) to investigate the effects of subways on city level outcomes are primarily or completely interested in ridership.[3] On the basis of a single cross-section of about 50 cities, Gordon and Willson (1984) conduct a city level regression to predict riders per mile of track as a function of city population density and country level per capita GDP. They find that these two variables are excellent predictors of ridership - the relationship being positive and negative, respectively. Barnes (2005) provides evidence from a few cities in the US that people are more likely to take transit for trips to a central business district than for trips to other locations. Finally, Baum-Snow and Kahn (2005) provide evidence from 16 US cities for a similar relationship between density and transit use, although their small sample size limits the precision of their results. They also show that ridership in catchment areas for new stations attains almost the same level as in the catchment areas of old stations over their 30 year study period. Consistent with the finding in Gordon and Willson (1984) that ridership decreases with income and increases with density, Baum-Snow and Kahn (2005) find that most US transit expansions have only small effects on ridership, a conclusion echoed in Gomez-Ibanez (1996) for time series data on the use of Boston's transit system. Our results on the relationship between subway extent are the first to exploit city level panel data.

B *Other infrastructure*

The literature relating roads and highways to urban growth has developed rapidly over the past several years and is surveyed in Redding and Turner (2015). This literature suggests the following

[3] We note the literature on modal choice using individual level data. This important literature is only tangentially related to our present inquiry. A survey is available in Small and Verhoef (2007).

conclusions.

First, that radial highways can have dramatic effects on the internal structure of cities. Baum-Snow (2007) investigates the effect of radial highways on population decentralization for a sample of large US cities between 1950 and 1990. He finds that, over the whole 40 year course of his study period, a single radial highway causes about a 9% decrease in central city population. This large decentralizing effect of highways is confirmed for China by Baum-Snow, Brandt, Henderson, Turner, and Zhang (2012) and for Spain by Garcia-López (2012).

Second, Duranton and Turner (2012) find that the stock of highways in a city contributes to the growth in city population in the US between 1980 and 2000. This effect is small in an absolute sense, though it is economically important as a share of the total growth rate. Using a similar research design, Garcia-López, Holl, and Viladecans-Marsal (2013) finds that highways cause about the same rate of population growth in Spanish cities.

Finally, Duranton and Turner (2011) find that traffic increases about proportionately to increases in the extent a city's road network, and that increases to non-commute individual driving appear to be the most important contributor to this increase. All of these responses, decentralization, growth and driving, can be detected over a 5-20 year time horizon, much shorter than our 60 year study period.

We find that the effects of subways on urban growth are qualitatively similar to those for roads. Any effect of subways on population growth is tiny. We find a much larger effect of subways on the configuration of cities. The effect of subways on ridership is large, though smaller than the effect of roads on driving. Finally, we will present indirect evidence to suggest that only a little of the increase in ridership reflects increased commuting.

We note that the relationship between highways and urban growth is better understood than is the relationship between subways and urban growth for two reasons. First, highways are pervasive and so even medium sized countries can provide statistically useful samples of cities. Second, the literature has devised credible instrumental variables strategies to deal with the non-random assignment of highways and railroads to cities. An analysis of subways, on the other hand, requires data from many countries to construct a reasonably large sample and there is little hope for quasi-random variation in the assignment of subways. Two important contributions of the present investigation are to overcome the data problem and to develop an identification strategy that relies on time series variation in panel data.

3. Data

To investigate the effect of subways on the evolution of a city's population and its spatial structure we require data describing subways, population and spatial structure for a panel of cities. We construct such data from four principal sources. Our population data are the UN World Cities

Data. Our subway data are the result of primary data collection, as is our ridership data. Our description of urban spatial structure derives from lights at night data.

A *Population data*

Our data are organized around the UN World Cities Data.[4] Produced by the United Nations, Department of Economic and Social Affairs, Population Division, these data describe population counts for all cities whose population exceeds 750,000 at any time during 1950-2010.

Constructing international data describing city level population is subject to two problems, the availability of population data and cross-country differences in the definitions of cities. Population data are generally available from decennial or quinquennial censuses. However, census years do not synchronize neatly across countries. To resolve this problem, the UN World Cities Data interpolate to construct annual values. Therefore, because few countries conduct censuses more often than every five years, successive annual population changes must sometimes reflect linear interpolation of the same proximate census years. To avoid making inferences from such imputed population changes, we restrict attention to observations drawn every fifth year, e.g., 1950, 1955, ..., and refer to each such observation as a 'city-year'. This decreases the likelihood that sequential city-years are calculated by interpolation from the same two underlying censuses. The method used to define metropolitan areas was to first obtain population counts at the most geographically disaggregated administrative unit available from every country. Once equipped with these data, metropolitan areas were defined as a a fixed set of smaller administrative units — regardless of whether the smaller units were in the same state for example. This allowed UN researchers to use a consistent definition of metropolitan areas across countries and over time, and captures what we think of as metropolitan areas.

The top panel of Table 1 describes our population data. The data consist of 632 cities, more than half in Asia. In 2010, the mean size of a city in our sample is about 2.4 million. There is little variation in mean size across continents, although cities in South America tend to be larger while cities in Europe tend to be smaller. Between 1950 and 2010, the mean five year growth rate of a city in our sample is about 18%. This rate falls by about 1% every five years. Not surprisingly, cities in Africa, Asia and South America grow faster than in North America and Europe. Europeans cities are the obvious outlier and grow more slowly than cities elsewhere. The growth rate of cities is declining on all continents and this decline is somewhat slower in Europe.

The bottom panel of Table 1 describes our population data for the 138 cities in our sample with a subway in 2010. At 4.7m people on average, these cities are dramatically larger than non-subway cities. Cairo is the single African city with a subway, and so the Africa column in the bottom panel of table 1 is really a 'Cairo column'. Australia has no subways in 2010. Asian and South American subway cities are larger than those in North America and dramatically larger than those in Europe.

[4] Downloaded from `http://esa.un.org/unup/GIS-Files/gis_1.htm`, February 2013.

The five year growth rate for an average subway city is about 11%, somewhat slower than in the whole sample. As for the whole sample, European subway cities are growing more slowly than other subway cities. Also similar to the whole population of cities, growth rates are declining by about 1% every five years and this decline is somewhat slower in Europe.

Table 1: Descriptive statistics for the world's cities and cities with subway systems in 2010

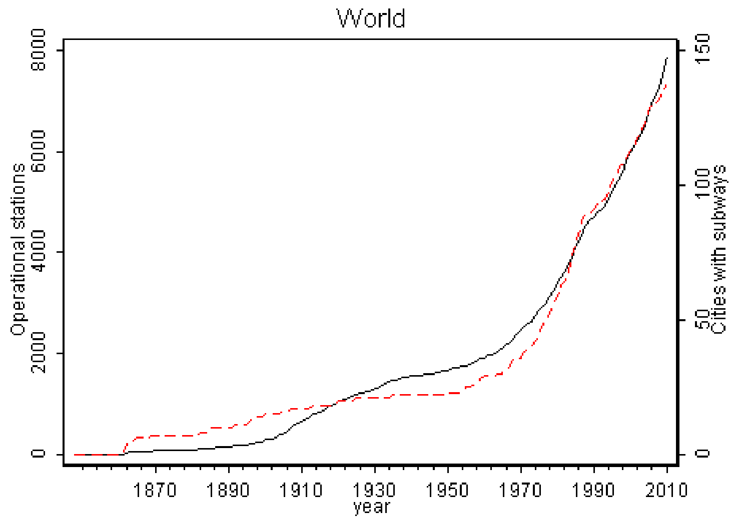
	World	Africa	Asia	Aus.	Europe	N. America	S. America
All cities							
N	632	73	341	6	57	99	56
Total Stations	7,886	51	2,977	0	2,782	1,598	478
Total route km	10,686	56	4,224	0	3,558	2,219	628
Population	2,427	2,104	2,511	2,429	1,921	2,441	2,825
log(Pop.)	14.329	14.296	14.325	14.572	14.227	14.344	14.450
Δ_t log(Pop.)	0.180	0.248	0.198	0.107	0.046	0.143	0.189
Δ_t^2 log(Pop.)	-0.010	-0.014	-0.008	-0.006	-0.005	-0.013	-0.015
Cities with subway in 2010							
N	138	1	53	0	40	30	14
Route km	77	56	80		89	74	45
Stations	57	51	56		70	53	34
Δ_t Stations	3.758	4.250	4.568		3.965	2.658	2.423
log(Stations)	3.551	3.932	3.505		3.872	3.332	3.252
Δ_t log(Stations)	0.204	0.101	0.305		0.158	0.140	0.117
Pop.	4,706	11,031	5,951		2,260	4,814	6,300
log(Pop.)	14.934	16.216	15.153		14.380	15.051	15.344
Δ_t log(Pop.)	0.113	0.124	0.144		0.045	0.123	0.170
Δ_t^2 log(Pop.)	-0.011	-0.014	-0.012		-0.005	-0.013	-0.017
Mean light in 25km disk	122	212	117		95	171	109
Corr. lights & pop.	0.67		0.67		0.69	0.78	0.91

Note: Population levels reported in thousands. Lights data are based on radiance calibrated lights at night imagery. All entries describing levels report 2010 values. Entries describing changes are averages over the period from 1950 to 2010.

B ***Subways data***

Our data describe the latitude, longitude and date of opening of every subway station in the world. These data were compiled 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. This process leads us to enumerate subway stations in 161 cities. Of

Figure 1: Growth of subway systems



Note: The dashed line indicates the number of cities with a subway system and the solid line indicates the total number of operational stations.

these, 138 are large enough to appear in the UN World Cities Data and are the main subject of our analysis.[5]

For our purposes, a 'subway' is defined as an electric powered urban rail 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, although we include underground streetcar segments. In order to focus on intra-urban subway transportation systems, we also exclude heavy rail commuter lines. We do not distinguish between surface, underground or aboveground subway lines as long as exclusive right of way condition is satisfied. These subways systems typically operate frequently, e.g., 10 minute headways or less during daytimes, are quick, reliable and are used mostly for the intra-urban transportation of people. For the most part, our subways 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 exclusions of particular marginal cases in our sample may be controversial.

We use our data to construct three measures of subway extent for each city-year. Most simply, we count the number of operational stations in each year. Since our data also enumerate subway lines, we also count the number of operational subway lines in each city in each year. Finally, by connecting stations on each subway line by the shortest possible route, we approximate the route of each subway line. Taking the union of all such lines in a city approximates each city's network. Calculating the length of this network gives us the length of each system. In this way we arrive at

[5]The 23 cities with subways in 2010 that do not occur in our population data because their population is too small are: Bielefeld, Bilbao, Bochum, Catania, Dortmund, Duisburg, Dusseldorf, Essen, Frankfurt, Genova, Hannover, Kitakyushu, Kryvyrih, Lausanne, Mulheim, Naha, Nuremberg, Palma, Perugia, Rennes, Rouen, Seville and Wuppertal.

our three primary measures of subway extent for each city-year; operational stations, operational lines and route kilometers.

Figure 2 illustrates our subway data for six cities. The figure shows all stations operational prior to 2013 as black dots. The network maps, on which the 2010 calculation of route km is based, are shown as black lines. Stations that opened after 2010 are not connected to the network. In each panel of the figure, a gray circle or ellipse describes a circle of 25km radius to show scale. That this circle is distorted in Northerly cities is a consequence of our map projection. To show the configuration of each city, the background shows lights at night in 2010. In the top row, with 2010 populations of 1.1m and 0.9m Tibilsi (Georgia) and Toulouse (France) are among the smallest cities in our sample to have subways. In 2010 their subway systems consist of 21 and 37 stations, and 27 and 28 route km. In the middle row, Boston and Singapore have populations of 4.7m and 5.1m, near the 4.7m mean for subway cities. Their subway systems consist of 74 and 78 stations and of 88 and 111 route km, which makes both systems somewhat larger than both world and the relevant continental averages. The bottom row of figure 2 shows two of the largest cities in our sample, Mexico City and Beijing. The population of Mexico City in 2010 was just over 20m against about 15m for Beijing. Their subway systems contained 147 and 124 stations and consisted of 182 and 209 route kilometers.

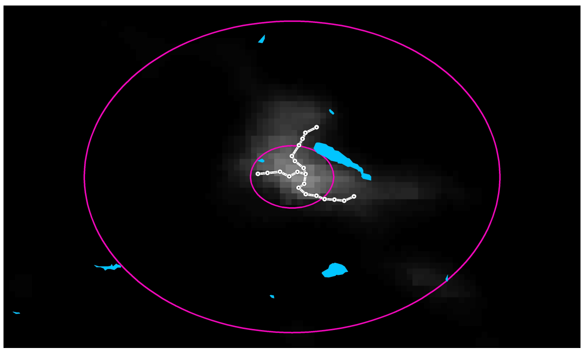
Figure 2 reveals two noteworthy features of our subways data. First, in each of the six cities, only a small portion of the city is within walking distance of a subway and the catchment area of the subway is centrally located. This is typical. An average city in our sample has about 57 stations. Of these, about 9% are within 1500m of the center, about 29% are between 1500m and 5km of the center, about the same share lie between 5 and 10km and between 10 and 25km. Just 7% of stations are beyond 25km from the center. Since the area to be served expands quadratically, this means that subways per square kilometer decreases rapidly in successive annuluses. In an average subway city, there are 0.67 stations per km^2 within 1500m of the center, 0.22 stations per km^2 between 1500m and 5km from the center, 0.07 stations per km^2 between 5 and 10km from the center, and 0.001 stations per km^2 between 10 and 25km from the center. Thus, in an average city, the preponderance of the subway system is located within 10km of the center and station density declines rapidly with distance from the center.

Close inspection of the network maps in figure 2 suggests that our networks probably diverge slightly from the actual network. The algorithm that we use to construct network maps connects all open stations on a subway line by the shortest possible route. Therefore, our measure of length is a measure of the route kilometers required to serve operational stations in each year rather than a literal measure of the length of track in the system.[6] While we regard the route kilometers

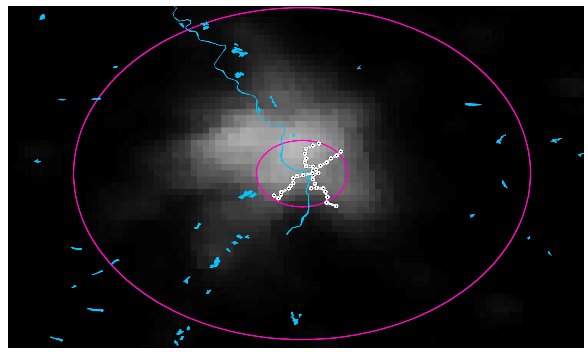
[6]Our algorithm will produce routes that diverge from the actual routes for four reasons. First, if pairs of stations are connected with curving track, the actual route will diverge from our straight line network. Second, if intermediate stations on a line open after the end points, then the algorithm will not include the intermediate stations on the network until they open. Third, we may mis-attribute stations to subway lines. Fourth, if a route is served by two or more sets of tracks — such as in New York city — then this replication is invisible to us.

measure as being of considerable interest, we suspect it is a noisier measure of subway extent than is the count of operational stations. Given this, our investigation relies primarily on the count of operational stations to measure system extent, although robustness checks show that our results are robust to our choice of subway measure.

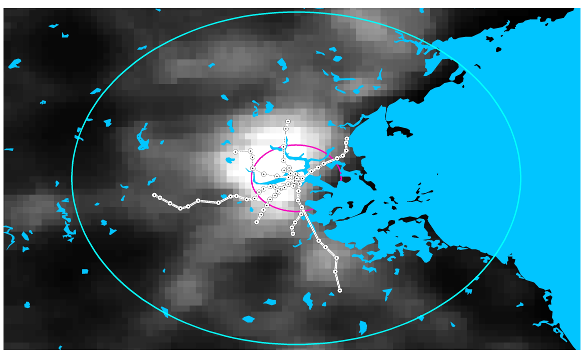
Figure 2: Lights and subways in 2010 for six cities



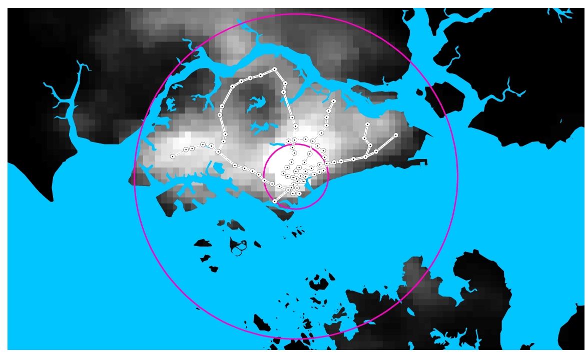
Tibilisi: 1.1m pop, 21 stations



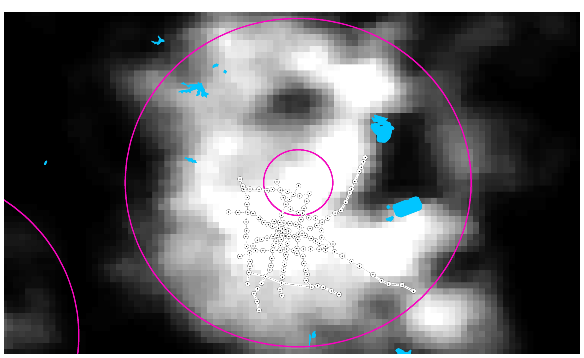
Toulouse: 0.9m pop and 37 stations



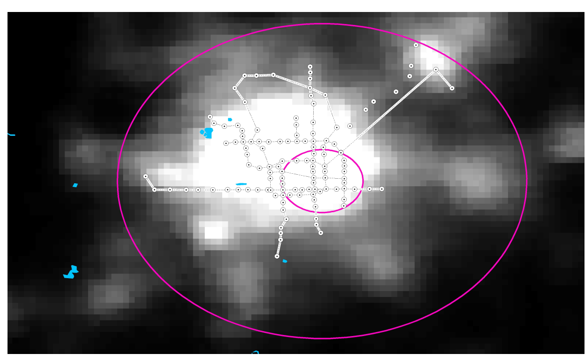
Boston: 4.7m pop, 74 stations



Singapore: 5.1m pop, 78 stations



Mexico City: 20.1m pop and 147 stations



Beijing: 15m pop and 124 stations

Note: Images show 2010 radiance calibrated lights at night, 2010 subway route maps and all subway stations constructed prior to 2010. The gray/pink ellipses in each figure are projected 5km and 25km radius circles to show scale and light gray/blue is water.

Table 1 presents descriptive statistics for the world's subway systems in 2010. In 2010 in our sample of cities, there were 7,886 operational subway stations and 10,686 route kilometers of subways, divided across 138 operational systems. Of these 138 subway cities, 53 are in Asia, 40 in Europe, 30 in North America, 14 in South America, one in Africa and none in Australia. Asia, Europe, North America and South America account for 38, 35, 20 and 6 percent of all operational stations in 2010. The corresponding percentages of route kilometers are 40 for Asia, 33 for Europe, 21 for North America and 6 for South America. Thus, Asia has more systems than Europe, but a typical system in Europe has more stations and route kilometers. North America accounts for a small share of subway stations and route km, it contains a small number of systems and the average extent of these systems is between that of Asian and European systems.

Table 1 reveals huge differences in the availability of subways across continents. Of the 341 large cities in Asia only 53, about 15%, have subway systems. In Europe, more than two thirds of large cities have subways, while in North America it is just less than one third. South America is a bit lower at 25%. Conditional on being in a subway city, the level of service also varies widely by continent. Cities are smaller and subway systems larger in Europe where there are 25,000 people per route km and 32,000 per station. These service levels are higher than those in North America and Asia and higher still than those in African and South American subway cities. Interestingly, although the share of North American cities with subways is much higher than in Asia, people per station and people per route km in subway cities are close for the two continents.

Two features of table 1 stand out. First, the huge gap in subway provision between Europe and the rest of the world. Second, the weak connection between mean city size and subway extent. In particular, Asia is home to the preponderance of the world's large cities while South America's cities are larger, on average, than those elsewhere. However, neither South America nor Asia is well provided with subways relative to Europe and North America. Indeed, Europe's cities are the smallest and it is by far the best provided with subways.

Figure A.2 illustrates the expansion of the world's subway systems over the past century. There were four subway systems in operation prior to or during 1860; Liverpool, Boston, London and New York. The "L" opened in Chicago in 1892 and The Paris Metro opened in 1900. Both the aggregate world data and the continental data, except for Asia, show a first wave of subway construction between the two world wars and a second wave beginning in the 1970s and continuing to 2010. The growth of Asian subways begins in the 1970s and has accelerated since. Except for North America, expansion of subway systems and increases in the number of subway cities track each other closely. In 2010, the 1,169 subway stations operating in the US were spread across 21 cities. However, 489 of these stations were in New York. Chicago is the second largest system at 142 stations. On average, the remaining 19 US subway cities have just 29 stations each.

C *Lights data*

Lights at night data are collected by earth observing satellites that measure the intensity of visible light every night in 30 arc second cells, about one kilometer square, on a regular grid covering the entire world. Most extant applications of the lights at night data in economics rely on the "DMSP-OLS Nighttime Lights Time Series".[7] These data are available annually from 1992 until 2012. Each of these lights at night images is a composite constructed from many raw satellite images and the value for each cell reflects average light intensity, over all cloud free images, on a scale of 0-62 with 63 used as a topcode. Since most large cities, particularly in the developed world contain large topcoded regions near their centers, these data are of limited use for studying the internal structure of the large wealthy cities where most subways are located. We instead exploit 'radiance calibrated at night data',[8] collected during times when the satellite sensor was set to be less sensitive. These data are less able to distinguish dim light sources, but are able to measure variation in light within regions that are topcoded in DMSP-OLS version. Fewer cross-sections of the radiance calibrated lights are available but, fortunately, the available cross-sections (1995, 2000, 2005 and 2010) match up neatly with the last four cross-sections of our population data.

Lights at night data are of interest as a check on our population data. The lights at night data are measured consistently across cities and we can calculate city level measures of total light without reference to administrative boundaries. That is, the lights at night data are not subject to either of the two problems that we are concerned about for our population data. Since people light the places they live and work, more densely populated and more productive places are often brighter. More concretely, Henderson and Storeygard 2012 use the topcoded version of lights at night data to show that country level mean light intensities are a good proxy for GDP, a result that Storeygard (2012) confirms at the regional level for China.

The last line of the bottom panel of table 1 shows the correlation of the mean 2010 light intensity within 25km of a city center in 2010 and 2010 population in subway cities. It is clear that lights provide some information about population, although this information is imperfect. Finally, we note that the lights at night data are difficult to interpret. While we can be confident that lights at night data are telling us something about the location of economic activity, we cannot know whether places are brighter because the people living there are richer, because the place is more densely populated, or because it is the site of a large office tower or factory.

Perhaps more importantly, the fine spatial resolution of the lights at night data allows us to examine the spatial structure of cities. In particular, we are able calculate measures which indicate the extent to which activity in the city is centralized or diffuse by calculating the gradient of average light in circles around a city center and its evolution over time. By using these sorts of measures, we are able to investigate the relationship between subways and urban form.

[7] Available from `http://www.ngdc.noaa.gov/dmsp/downloadV4composites.html` (October 2014). We are grateful to Alexi Abrahms for drawing our attention to these data.

[8] Downloaded in October 2014 from `http://ngdc.noaa.gov/eog/dmsp/download_radcal.html`.

D *Public transit ridership data*

We collected panel data on public transit ridership for the cities in our database from publicly available sources and reports. We were able to obtain data on 77 subway systems and 40 bus transit systems.[9] Table 2 shows ridership descriptive statistics for subways and buses in 2010. Bus systems provide on average 250 million trips per year, whereas subways provide on average 377 million trips per year. In per capita terms (columns 4-8), subways and buses are about equally important in terms of rides per person per year. This is true not only when comparing averages, but also when comparing cities for which both types of ridership information are available.

Table 2: Public transit ridership (2010)

	Annual ridership (millions of rides)				Annual ridership per capita (rides per person per year)					
	Mean	Std. dev.	0.10	0.90	Mean	Std. dev.	0.10	0.90	Cities	Countries
Subway	377	640	18	1,110	69	76	8	127	77	34
Bus	242	343	26	697	67	80	12	170	40	17
Bus $\mid$ Subways>0	256	315	36	584	74	86	14	145	31	17

Source: American Public Transportation Association, public transit agencies, municipal and state-level statistics agencies, and railway companies.

4. The relationship between subways and population

We now turn to a description of the relationship between subways and population. Figure 3 shows the relationship in 2010 between city size and the incidence of subway systems for all of the cities in our sample excluding Tokyo.[10] The horizontal axis gives city population by 0.5m bin and the vertical axis gives the proportion of cities with subways for each bin. We split our sample of cities into rich and poor country cities on the basis of the IMF advanced economy list for 2012.[11] Grey squares and black triangles indicate the share of rich and poor country cities with subways. The markers are spaced irregularly along the horizontal axis because some population bins are empty. The solid line is a smoothed plot of subway frequency in rich country cities and the dashed line is the corresponding plot for poor country cities.[12]

There are no rich country cities with population above 5m without a subway system and subways are common even among rich country cities with populations in the 1m-5m range. Subways

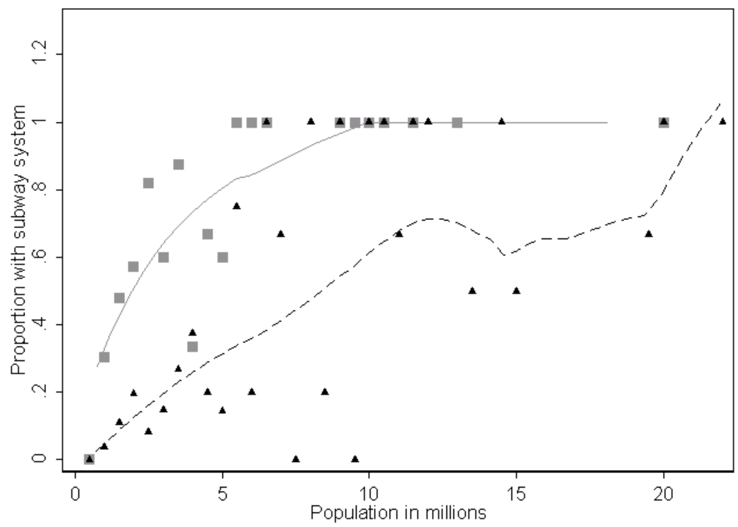
[9] Information on bus ridership by year is only reported by integrated transit systems, something that is not common in developing countries. In particular, we have no bus ridership data for cities in Africa and South America.

[10] At 36 million people, Tokyo is nearly twice as large as the second largest city. We omit it from the figure to improve legibility.

[11] These rich countries are: Australia, Japan, New Zealand, the United States, Canada, Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Netherlands, Norway, Portugal, Singapore, South Korea, Spain, Sweden, Switzerland and the United Kingdom.

[12] More specifically, both lines are kernel weighted local polynomial regressions.

Figure 3: Proportion of cities with subways systems by population for two income classes



Note: Gray squares correspond to rich country cities and black triangles to poor country cities. See footnote 11 for the list of countries.

are relatively rare among developing country cities with populations less than about 5m and their frequency increases more or less smoothly with city size.

Table 3 describes the largest 90 cities in our sample as of 2010. For each city, the table reports population, the count of operational stations and the number of stations per 100,000 of population. Despite the strong relationship between city size and the presence of a subway system that we see in figure 3, table 3 suggests that the relationship between population and subways is nuanced. In particular, none of the four cities larger than New York has even half as many subway stations. Looking down the list, we see that such reversals are common and do not simply reflect rich and poor country differences. Consistent with this, the raw correlation between operational stations and population in 2010 is about 0.58. While subways are clearly more common in big cities, the relationship between system size and city size is noisy. Table 3 further suggests that subway capacity is rarely, if ever, a binding constraint on city size. Indeed, some of the world's largest cities have no subway system to speak of.

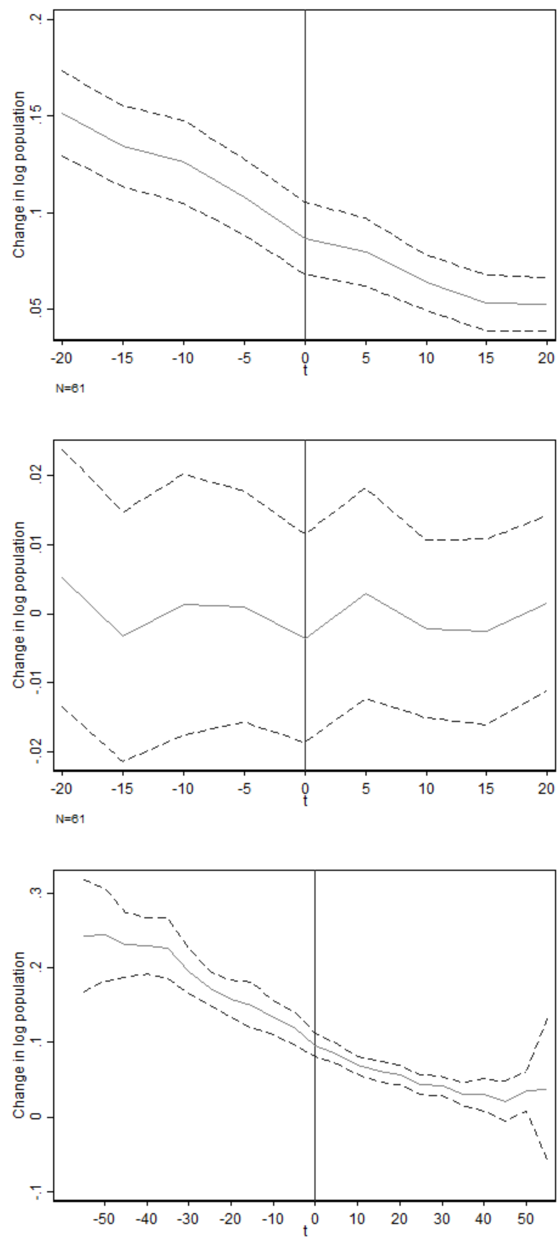
We now turn to an investigation of what happens to a city when its subway system changes. Figure 4 presents three panels describing the relationship between changes in population and subway system extent. The horizontal axis of each panel is time in years since a subway system opening, with negative values indicating years prior and conversely. The vertical axis indicates the mean change in log population, the population growth rate, for all cities during the five year period ending t years before or after the subway opening. The solid line plots the mean growth

Table 3: Population and subway stations for the world's 90 largest cities as of 2010.

City Name	Pop.	Stations	Stations pp.	City Name	Pop.	Stations	Stations pp.
Tokyo	36,933	255	0.69	Ho Chi Minh City	6,189	.	.
Delhi	21,935	128	0.58	Miami	5,971	22	0.37
Mexico City	20,142	147	0.73	Santiago	5,959	93	1.56
New York	20,104	489	2.43	Baghdad	5,891	.	.
Sao Paulo	19,649	62	0.32	Philadelphia	5,841	64	1.10
Shanghai	19,554	239	1.22	Nanjing	5,665	54	0.95
Mumbai	19,422	.	.	Haerbin	5,496	.	.
Beijing	15,000	124	0.83	Barcelona	5,488	137	2.50
Dhaka	14,930	.	.	Toronto	5,485	69	1.26
Kolkata	14,283	23	0.16	Shenyang	5,469	22	0.40
Karachi	13,500	.	.	Belo Horizonte	5,407	19	0.35
Buenos Aires	13,370	76	0.57	Riyadh	5,227	.	.
Los Angeles	13,223	30	0.23	Hangzhou	5,189	.	.
Rio de Janeiro	11,867	35	0.29	Dallas-Fort Worth	5,143	.	.
Manila	11,654	43	0.37	Singapore	5,086	78	1.53
Moscow	11,472	168	1.46	Chittagong	5,069	.	.
Osaka	11,430	125	1.09	Pune	4,951	.	.
Cairo	11,031	51	0.46	Atlanta	4,875	38	0.78
Istanbul	10,953	12	0.11	Xi'an, Shaanxi	4,846	.	.
Lagos	10,788	.	.	Saint Petersburg	4,842	63	1.30
Paris	10,516	299	2.84	Luanda	4,790	.	.
Guangzhou	10,486	123	1.17	Houston	4,785	.	.
Shenzhen	10,222	47	0.46	Boston	4,772	74	1.55
Seoul	9,751	360	3.69	Washington, D.C.	4,634	86	1.86
Chongqing	9,732	.	.	Khartoum	4,516	.	.
Jakarta	9,630	.	.	Sydney	4,479	.	.
Chicago	9,545	142	1.49	Guadalajara	4,442	17	0.38
Lima	8,950	16	0.18	Surat	4,438	.	.
London	8,923	267	2.99	Alexandria	4,400	.	.
Wuhan	8,904	25	0.28	Detroit	4,364	12	0.27
Tianjin	8,535	36	0.42	Yangon	4,356	.	.
Chennai	8,523	.	.	Abidjan	4,151	.	.
Bogota	8,502	.	.	Monterrey	4,100	32	0.78
Kinshasa	8,415	.	.	Ankara	4,074	12	0.29
Bangalore	8,275	.	.	Shantou	4,062	.	.
Bangkok	8,213	51	0.62	Salvador	3,947	.	.
Hyderabad	7,578	.	.	Melbourne	3,896	.	.
Lahore	7,352	.	.	Porto Alegre	3,892	17	0.44
Tehran	7,243	54	0.75	Phoenix	3,830	.	.
Dongguan	7,160	.	.	Montreal	3,808	68	1.79
Hong Kong	7,053	54	0.77	Zhengzhou	3,796	.	.
Madrid	6,405	239	3.73	Johannesburg	3,763	.	.
Chengdu	6,397	16	0.25	Brasilia	3,701	27	0.73
Ahmadabad	6,210	.	.	Recife	3,684	28	0.76
Foshan	6,208	.	.	San Francisco	3,681	48	1.30

Note: Populations in thousands. Subway stations per person is per 100,000 residents.

Figure 4: Subways openings population growth



Note: (Top) Mean population growth rates by time from system opening, constant sample. (Middle) Mean deviation from annual population growth rates by time from system opening, constant sample of cities. (Bottom) Mean population growth rates by time from system opening, long time horizon.

Table 4: Mean city-year population growth rates by time to a subway expansion

	$t-2$	$t-1$	t	$t+1$	$t+2$	N
Panel a						
			0.063	0.054***		138
			0.078	0.067**	0.064**	60
		0.090***	0.073			204
	0.120**	0.107***	0.083			141
		0.075***	0.061	0.052**		64
Panel b						
				−0.001		138
				−0.001	−0.009	60
		0.006*				204
	0.013*	0.012*				141
		0.009*		−0.007		64

Notes: Each row in panel (a) shows growth rates of cities in consecutive time periods. Each row in panel (b) shows the difference in growth rates of cities (relative to period t) in consecutive time periods from a regression controlling for year×continent dummies. t is a period of subway expansion. $j \neq t$ is a period with no subway expansion. Stars indicate a significant difference of growth rate compared to period t. *** 1%, ** 5%, * 10% significance respectively.

rate and dashed lines give upper and lower 95% confidence bounds.[13]

The top panel of figure 4 shows the average population growth rate of cities as a function of the time since their subway system opened. This figure is based on data describing the 61 cities that opened their subway between 1970 and 1990, the set of cities for which we can calculate population growth rates both for 20 years before and after their subway opens. This figure shows that the average population growth rate during the five years following the opening of a subway system is about 8%. During the five year period preceding a subway opening by five years, the average population growth rate is about 12%. During the 20 years before and after a subway opening, the average city in our sample sees its growth rate decline and there is no obvious change in this trend around the opening of the subway system.

The decrease in population growth rates visible in the top panel probably reflects the sample wide decrease in growth rates documented in table 1. It may be that this downward trend masks increases in growth rates associated with subway system openings. The middle panel of figure 4 investigates this possibility by controlling for each period's mean growth rate. Using the same sample as in the top panel, for each year we calculate each city's residual growth rate from a regression of growth rates on continent and year dummies. We next calculate the average of these residuals as a function of time from subway opening. Unsurprisingly, this process removes the downward trend that we see in the first three panels. Perhaps more surprisingly, it still does not show a systematic change in growth rates following subway system openings.

[13] These are local bounds are constructed by connecting upper and lower 5% bounds at each year.

The top two panels of figure 4 show that city population growth rates do not increase during the 20 year period following the opening of a subway system. As we discuss in section 2, the literature documents effects of subways on within city outcomes over much shorter periods and the effects of other types of infrastructure on city level outcomes over a 10-20 year horizon. Thus, the 40 year period illustrated in the top two panels of figure 4 should be long enough to reveal whether growth rates respond to a subway system opening. To explore the issue further, in the bottom figure we use our entire sample of cities and investigate population growth rates over the longest time period that our 60 year sample allows, 55 years. This figure suggests that the pattern we see in panel (a) extends nearly 55 years before and after a subway opening, although our estimates become noisier as the time from the subway opening approaches 55 years.

To check for differences across regions in the relationship between urban growth and subways, we also reproduce these figures continent by continent (not shown). Remarkably, each of the continents shows a similar pattern. Urban population growth rates decline in the period around subway openings and there is no obvious sign of a change in this trend at the time a subway opens. The only qualification of this statement applies to Europe, where there is a statistically insignificant positive deviation from trend around the opening of a subway system. We have reproduced the top two panels of figure 4 figures restricting attention to cities with population above 1m in 1970. This eliminates the small fast growing cities that qualify for the sample late in the sampling period. The resulting figures are difficult to distinguish from those in figure 4.

Figure 4 describes population growth rates as time varies relative to the date of a subway system *opening*. In Table 4 we turn our attention to the relationship between subway *expansions* and growth rates. The top row of panel (a) describes 138 city-year pairs where a city-year with a subway expansion is followed by a city-year without a subway expansion. On average, the growth rate in city-years with an expansion is 0.063, and in the subsequent city-year, without an expansion, it is 0.054. A t-test of the difference between the two means indicates that they are statistically different with high probability. In short, population growth rates are lower following a subway expansion than during one.

The remaining three rows of panel (a) of table 4 perform similar calculations for slightly different sets of city-years. In row two we consider the 60 city-year triples for which we observe a subway expansion followed by two city-years without an expansion. As for row 1, we see that growth rates decline following a subway expansion and that the decrease in growth rate is statistically different from zero. In the third row we consider the 204 pairs of city-years where a subway expansion follows a city-year without an expansion. The mean growth rate for city-years preceding a subway expansion is larger than for city-years with an expansion, and this difference is statistically different from zero. The fourth row of table 4 considers the 141 triples of city-years where a subway expansion is preceded by two years without an expansion. Again, we see that city growth rates decline in the years leading up to a subway expansion. The last row of table 4 considers the 64 triples of city-years for which a subway expansion follows and precedes city-years without expansions. The pattern of the other rows is preserved. Population growth rates are higher before a subway expansion and lower after, and this trend is statistically different from zero.

Similarly to the middle of figure 4, panel (b) of table 4 replicates the results of panel (a), but controls for continent and year fixed effects. Specifically, the values reported in panel (b) of table 4 are regression coefficients β from the regression,

$$\Delta log(\text{Pop}_{it}) = \alpha_t + \phi \cdot \text{Continent Dummy}_j + \beta \cdot \text{Time to Expansion Indicators}_{it} + \epsilon_{it},$$

which we estimate with robust errors, clustered at the city level, using the same samples as in the top panel. We test whether the various time to expansion coefficients are different from the year zero coefficient using a robust F-test. Even after we control for year and continent fixed effects, subway expansions are not associated with a measurable change in population growth rates.

5. Econometric model

The descriptive evidence presented so far indicates a positive cross-sectional relationship between the extent of a city's subway network and its population. Larger cities have more extensive subway networks. On the other hand, time series evidence suggests that changes to subway networks do not affect the population of cities. These facts suggest that large cities build and expand subway networks but that these networks do not cause changes in subsequent population growth. To establish this causal interpretation of the patterns we see in the raw data, we must address two main inference problems, the problem of confounding dynamics and the problem of omitted variables.

A *The problem of confounding dynamics*

Confounding dynamics arise if subway extent and population evolve such that subways open or expand in years that are, on average, different from other years. Many examples are possible. For example, it may be that cities tend to build and open subways as some constraint to their growth begins to bind and their growth is slowing. In this case, these cities might have seen a dramatic decline in growth had they failed to construct a subway but manage to maintain their growth by adding to their networks. Alternatively, it may be that city population naturally declines when subways open as construction workers leave, and positive effects of subways on growth just offset this loss.

More generally, this class of problems arises when there is some series of population shocks that systematically precedes an expansion of the subway network and confounds naive estimates of the relationship between subway expansion and growth. Describing the problem in this way suggests two possible responses. The first is simply to control for the history of population growth in the period leading up to a subway expansion. In this way, we can estimate the effect of subways, holding constant their population growth during the preceding periods. The second is to find an instrument that predicts subway expansions but is conditionally orthogonal to the hypothetical sequence of confounding population shocks.

As we will see, subway systems grow along a very predictable trajectory (see appendix figure A.2) and so long lags of subway growth are good predictors of current subway growth. By construction, long lags of subway growth pre-date the hypothetical confounding recent history of population growth, and it is plausible that they satisfy the relevant exclusion restriction.

In the remainder of this section we develop an econometric model that allows us to make this intuition precise and will form the basis for subsequent estimations. To begin, index the set of observed cities by $i \in I$ and the set of observed years by $t \in T$. Let y_{it} denote an outcome of interest for city i in year t. Depending on context, y will be population, light intensity within a radius of the city center, a measure of the centrality of the city or a measure of ridership. Let s_{it} denote a measure of subway extent in city i in year t, usually the number of operational stations but sometimes the number of operational subway lines or route kilometers. Let x_{it} denote a vector of time varying city level covariates, most often country level GDP per capita and continent specific year indicators, and z_i a time-invariant vector of city level controls. We use the operator Δ to denote first differences, so that $\Delta x_t = x_t - x_{t-1}$.

We do not have a strong prior over whether subways should affect city population levels or growth rates additively or multiplicatively. Appendix figure 9 shows plots of population growth against subway growth in both logarithms and levels. The figures clearly suggest that the logarithmic forms better represent the data. Given this, henceforth, quantities are typically in logarithms and where necessary we add one to variables to facilitate this transformation. This also allows us to interpret regression coefficients as elasticities.

In light of the differences between the time series and cross-sectional relationship between subways and population growth, we are also concerned that cities have time invariant characteristics correlated with size and subway extent. The following system, while too stark to be defensible, formalizes this problem and allows a discussion of how our lagged subways instrument address the problem of confounding dynamics.

$$y_{it} = A_1 s_{it} + c_i + \epsilon_{it} \tag{1}$$

$$s_{it} = B_1 s_{it-k} + d_i + \eta_{it}, \tag{2}$$

where A_1, the "outcome elasticity of subway extent", is the parameter of interest and k is a positive integer. In words, population depends on contemporaneous subways, a city specific intercept and a random disturbance. Subways at t depend on subways at period $t - k$, a city specific intercept and a random disturbance.

Written this way, it is natural to consider using s_{it-k} as an instrument for s_{it}. This is subject to two objections. First, this system of equation commits us to a particular dynamic structure for the relationship between subways and population. It is natural to wonder whether this dynamic structure is correct. In our estimations we consider alternative dynamic structures for our data. Second, unobserved time invariant determinants of subway construction are probably related to unobserved time invariant determinants of growth. That is, $cov(c_i, d_i) \neq 0$. It follows that, because s_{it-k} also depends on d_i, we should not expect $cov((c_i + \epsilon_{it}), s_{it-k}) = 0$. That is, the dynamic structure described by equations (1) and (2) requires that s_{it-k} be correlated with unobservables in the population equation, and thus, that it is not a valid instrument in this context.

As a first response to this problem, first difference equations 1 and 2 to get

$$\Delta y_{it} = A_1 \Delta s_{it} + \Delta \epsilon_{it} \quad (3)$$

$$\Delta s_{it} = B_1 \Delta s_{it-k} + \Delta \eta_{it}. \quad (4)$$

Differencing solves two problems. First, and as usual, it removes time-invariant unobservables from the first equation.[14] Second, after removing the city specific intercept from the population equation, the validity of lagged subways as an instrument for current subways hinges on the whether $cov(\Delta s_{it-k}, \Delta \epsilon_{it}) = 0$, or in words, on whether lagged change in subways is uncorrelated with current change in the time varying propensity to grow. This is simply a more technical statement of the intuition that motivates this instrumental variables strategy.[15]

The discussion above describes an econometric strategy based around using old subway system extent to instrument for current subway system growth. An alternative is to use lagged changes of population to instrument for current changes in subways. The basic logic of this approach is similar to that described above. However, lagged population levels and changes have less ability to predict current changes to subways than do lagged subway variables, so we organize our discussion and analysis around the lagged subways instruments.

The instrumental variable strategy articulated above responds to the possibility that subway construction reflects recent trends in population. A similar problem arises if both population growth and subway growth reflect some unobserved city specific time-varying factor. For example, it may be that poor administrations make cities grow slowly and also build subway networks. In this case, our estimated effect of subways on population growth confound the effects of bad municipal government with the effects of subways. To address this possibility, we would like to include fixed effects in the first differences regressions, or equivalently, city specific trend in the levels regressions, equations (1) and (2). To implement this estimator, we second difference equation (1).[16]

[14]While differencing solves one problem, it may create another. If $k = 1$ then both Δs_{it-1} and Δy_{it} involve terms for quantities for time t. If we are concerned about contemporaneous correlation of errors in the population and subway equations, then this creates an obvious problem. This is a classic problem in dynamic panel data and the conventional approach is to substitute s_{it-2} for Δs_{it-1} or to use longer lags.

[15]We note that the instrumental variables strategy described here is related to the one proposed by Olley and Pakes (1991), while the exogeneity condition of equation 4 is related to ideas developed in Arellano and Bond (1991).

[16]In principle, one could also implement our instrumental variables strategy in second differences. We experimented with this but found that lagged subways and population variables do not have much ability to predict current second differences of subways. Consequently, these regressions were not informative.

Summarizing, our econometric investigation will be organized around estimating the following system,

$$y_{it} = A_1 s_{it} + A_2 x_{it} + A_3 z_i + c_i + g_i t + \epsilon_{it} \quad (5)$$

$$s_{it} = B_1 s_{it-k} + B_2 x_{it} + B_3 z_i + d_i + h_i t + \eta_{it}. \quad (6)$$

This generalizes equations 1 and 2 in a number of ways. First, it allows for time-invariant control variables, z_i. Second, it allows for city specific trends and intercepts in both population and subways equations. Third, it allows for time varying controls, lags of y_i in particular. In practice, we predict current changes in subways with 20 or 40 year old subways changes, so that $k = 4$ or 8.

B *The problem of omitted variables*

Our second main inference problem is omitted variables. Again, many examples are possible. For example, suppose that in every year that a city does not invest in subways, it invests in buses or roads, and that buses, roads and subways substitute perfectly for each other. In this case, years with subway expansions will be identical to years without, even though subways may be having an arbitrarily large positive effect on population growth. Moreover, in this example, our lagged subways instrument will fail to resolve this problem, since it is also correlated with growth in buses.

Our data allows us to deal with this particular concern by controlling for changes in bus ridership, but for roads we observe only a single cross-section near the end of our study period. Given this, we check whether subways affect cities with extensive road networks differently from those without. The logic for this test follows from the example above. If roads are a substitute for subways, then a first difference regression should reveal a smaller effect of subways in cities with extensive road networks than those without. Intuitively, years with subway expansions should be more like other years if those other years were occupied by road building. This is more likely in cities that finish the study period with an extensive road network.

More formally, we estimate the following regression

$$\Delta y_{it} = A_1 \Delta s_{it} + A_2 (\Delta s_{it} \times x_i) + \Delta \epsilon_{it} \quad (7)$$

where x_i denotes the terminal value of some control variable omitted from our main specification. The particular variables that we consider measure: topography; the terminal stock of roads; capital status; post WWII subway system indicator; degree of centralization; road congestion levels; and an ease of doing business index, among others.[17]

[17] We do not have a strong prior over whether or not the variable x_i should occur independently in this equation. It is conventional that this it should do so, however, since this is a first difference regression and since the x_i's do not vary over time, the first difference of a regression in levels that included an independent x_i term would look like equation 7. As a practical matter, we report estimates of equation 7, but corresponding estimates that include and independent term in x_i do not lead to important differences in our estimates of the effects of subways on population growth.

6. Subways and population: Main estimation results

We proceed by estimating successively more complete and complex versions of equations 5 and 6. To begin, in table 5 we estimate equation 5 using OLS on pooled cross-sections. Such estimations result in unbiased estimates only if the time invariant determinants of subways and population are uncorrelated. This condition seems implausibly strong. We expect that unobserved factors affecting the attractiveness of a city also affect its construction of subways, so we regard these estimations as primarily descriptive.

In column 1 of table 5 we regress the log of population on log of the count of operational subway stations. We use the entire sample of 632 cities for which we have population and subway data. Since our panel is complete for these two variables, we have a sample of $13 \times 632 = 8{,}216$ city-years. The subway elasticity of population is large. A 10% increase in a city's count of stations is associated with a 4.8% increase in population. Column 2 replicates this result, but controls for country level GDP and continent-by-year fixed effects, along with several time-invariant controls; a capital city indicator, and distances to the ocean, international boundary and nearest navigable river. We see that the coefficient on subways, while still large, decreases to 0.28. Our sample size decreases to 7,374 in this regression, primarily because a number of the countries covered by our sample, particularly those in the former Soviet Union, came into existence after 1950 and so country level GDP is not available.

Column 3 considers the same regression as column 2, but restricts attention to cities that had subways in 2010. This is the largest sample of cities that could possibly contribute to a first differences estimate of the effect of subways. This reduces our sample size to 1,565 city-years, but leaves the coefficient of subways almost unchanged. The sample of 137 cities used in column 3 includes some cities that were small in 1950 and grew quickly to cross the 750,000 threshold for inclusion in the UN World Cities Data. Columns 4 and 5 replicate column 3, but consider alternative measures of subway extent, route kilometers and log subway lines. Coefficient magnitudes change approximately in proportion to the changes in the standard deviation of the subway measures. Thus, our cross-sectional estimates are not artifacts of our particular measure of subway extent.

In all of the regressions reported in table 5 we test for and fail to reject serial correlation of order 1, and of orders 2 and 3 for the longer population panels. This indicates the presence of a dynamic structure not described by the pooled cross-section specification.

Table 5: Pooled cross section

	All cities		Subway cities			
	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(\text{pop}_t)$	$\ln(\text{pop}_t)$	$\ln(\text{pop}_t)$	$\ln(\text{pop}_t)$	$\ln(\text{pop}_t)$	$\ln(\text{Lights}_t)$
$\ln(s_t)$	0.48^{***}	0.28^{***}	0.26^{***}			0.17^{***}
	(0.02)	(0.03)	(0.03)			(0.03)
$\ln(\text{route km}_t)$				0.23^{***}		
				(0.03)		
$\ln(\text{subway lines}_t)$					0.52^{***}	
					(0.06)	
$\ln(\text{GDP}pc_t)$		0.31^{***}	0.02	0.03	0.01	0.37^{***}
		(0.04)	(0.09)	(0.09)	(0.09)	(0.08)
$\ln(\text{COUNTRY POP}_t)$		0.17^{***}	0.28^{***}	0.29^{***}	0.27^{***}	0.20^{***}
		(0.03)	(0.05)	(0.06)	(0.06)	(0.05)
Geographic controls	No	Yes	Yes	Yes	Yes	Yes
YearXContinent dummies	No	Yes	Yes	Yes	Yes	Yes
Mean of Dep Variable	13.35	13.44	14.48	14.48	14.48	4.67
Mean of subways regressor	0.38	0.40	1.88	1.99	0.79	3.06
SD subways regressor	1.15	1.17	1.92	2.05	0.91	1.49
R-squared	0.18	0.49	0.53	0.52	0.53	0.54
Number of cities	632	627	137	137	137	137
Number of subway cities	138	137	137	137	137	137
Number of periods	13	13	13	13	13	4
Observations	8216	7374	1565	1565	1565	548

Dependent variable: Log population of metropolitan area in period t (except last column see (9) below).
City-level clustered standard errors in parentheses. Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.
Geographic controls are capital city dummy, log km to ocean, log km to land border, and log km to major navigable river.

(1)- Pooled cross section.

(2)- Add geographic controls, GDP pc control, country population, and year-by-continent dummies.

(3)- Restrict sample to cities with subway by 2010. (4) Log route km of subways as main regressor.

(5)- Log subway lines in system as main regressor.

(6)- Dep. var. is log mean radiance calibrated lights in a 25km circle around the centroid of the city.

Column 6 reports a regression similar to column 3, where our dependent variable is the logarithm of mean light intensity in a 25 km disk centered on the city. As in column 3, we restrict attention to cities with subways in 2010. Our sample of city-years is smaller than for population regressions because we have just four cross sections of lights data. We see that a one percent increase in subways is associated with a 0.17 percent increase in lights. This is close to our results for population and suggests that our population regressions are not driven by problems in the UN World Cities Data. In sum, table 5 confirms the conclusion of figure 3. Cities with more subways tend to be bigger. This relationship is robust to time-invariant controls, sampling, the particular measure of subway extent and whether we measure city size with lights or population.

We now turn to first difference regressions. Table 6 presents first difference estimates of a version of equation (5) without city specific trends. We note that both first difference and within estimators are consistent estimators for equation (5) if the errors, ϵ_{it} in each period are not correlated with the regressors in any period conditional on the unobserved effect. Because our approach to estimating equations (5) and (6) revolves around first difference estimations, we prefer the first differences estimator.[18]

Columns 3-6 in table 6 use the same sample of cities as column 2 of table 5, while columns 1 and 2 use the slightly larger sample available when we do not control for changes in GDP. In column 1, we report the results of regressing change in log population on change in the log of the count of operational stations. In column 2 we repeat this regression with continent specific year dummies. These estimates approximately correspond to the top and bottom panels of table 4 except that they are sensitive to the magnitude of the subway expansion, where table 4 just reports means conditional and subway expansion or not. Like table 4 we see a negative relationship between subway expansions and population growth when we do not control for continent specific year effects, but that the relationship between subways and population is approximately zero once we include these controls.

In column 3 we add controls for country level changes in GDP and POPULATION and in columns 4 and 5 we measure subway extent using route km and counts of subway lines. In every case, we estimate the effect of subways to be less than 0.01 with standard errors around 0.003. That is, these are tiny effects, precisely estimated. In column 6 we replicate column 4 but use 10 year rather than five year intervals to calculate our study periods, while in column 6 we report a long difference regression where we conduct a cross-sectional regression of long difference of population on long differences of subways. Both point estimates are small negative numbers but neither is distinguishable from zero at ordinary levels of confidence. Columns 6 and 7 suggest that

[18]The choice between the two estimators hinges on subtle differences in the errors. The first difference estimator is more efficient if ϵ_{it} is a random walk, while the within estimator is more efficient if the ϵ_{it} are i.i.d. (Ch. 10, Wooldridge (2001)).

our first difference estimates are not an artifact of the frequency with which we sample the data.[19]

In column 8 we use the average light intensity in a disk of 25km centered on the city as our dependent variable. As with our other regressions, we find a much smaller effect than in the comparable cross-sectional regression, column 8 of table 5, in this case not distinguishable from zero. Finally, in column 9 we control for our measure of bus ridership. Since the sample of cities and years for which we observe bus ridership is much smaller than the sample for which we observe subways and population, our sample of years and cities shrinks considerably. However, including this control does not lead to a positive effect of subways on population. In fact, the relationship is slightly negative.

Summing up, first difference estimates are dramatically smaller than cross-sectional estimates and the only point estimates distinguishable from zero are, in fact, negative. Not only are the estimates of the effect smaller than those in the cross-sectionnal estimates, but they are very small in an absolute sense, in every case but lights, well under 1% and in columns 1-6, very precisely estimated.

We now turn to the possibility of confounding dynamics. Columns 1 and 2 of table 7 replicate column 3 of table 7 while controlling for for the second and third lag of population change. Our sample size drops slightly in these specifications because we observe lagged population for fewer city years than we observe contemporaneous population. Like the corresponding first difference regression in table 6, these regressions indicate tiny and precisely estimated effects of subways on population growth. Because the first lag of population is mechanically endogeous in our first difference regressions, columns 1 and 2 of table 7 control for the second and third lags of population. Column 3, instead reports second difference regressions. If there are city specific trends, this regression will account for this. As in the first difference regressions, we see a tiny precisely estimated relationship between subways and population.

In the remainder of table 7 we turn attention to the instrumental variables regressions described in section 5. That is, we replicate our first difference regressions but use the fourth or eighth lag of subways as an instrument for the current change. The appendix describes the first stage. As we see in appendix figure A.2, subway systems grow very predictably, and at a decreasing rate. Thus, given the growth rate of a subway system in any period, we can forecast the future, lower, growth rate quite accurately. This is demonstrated in table A.1 which presents first stage results predicting current subway system growth rate as a function of lagged subway size and the controls that appear in the first two columns of table 7. We see that our instruments are not weak, and behave as we would expect given the profile of system growth that we see in figure A.2.

In columns 4 and 5 of table 7 we replicate column 1, but instrument for change in subways with the fourth lag log subways. In column 6 we replicate column 1 but instrument for change

[19]In fact, the frequency with which we sample the data can create problems with our estimates. If we conduct a long difference regression from 1950-2010, we get a statistically significant positive relationship between subways and population. This result is driven entirely by two cities which grew rapidly over the whole period and built large subway systems between 2005 and 2010. Excluding these two cities restores a coefficient of about zero in this regression.

in subways with the eighth lag of log subways. The IV point estimates of the effect of subways are slightly larger than the first difference estimates, but never above 2% and never statistically distinguishable from zero. In sum, to the extent that we are able to check, table 7 does not support the hypothesis that subways have a large positive effect on population growth that is masked by some confounding dynamic process.

We next consider models that allow for a distributed lag structure in our data. In column 1 of table 8, we replicate column 3 of table 6 and in columns 2-4 we substitute successively older lags of change in subways for the current value. Like the effects of current subways, the effects of lagged subways are tiny and precisely estimated. In column 5 we include the the current change of subways and three lags and see that coefficients are virtually identical to those we obtained when we include subway variables one at a time. This suggests that our focus on the relationship between current subway expansions and current population growth is not leading us to miss some longer term effect of subways on population growth. These regressions suggest that a subway expansion does not affect current or future rates of population growth.

We now turn attention to the problem of omitted variables using the strategy described in equation (7). In column 1 of table 9 we replicate the first difference regression from column 3 of table 6 for reference. In column 2 we include an interaction between subways and an indicator for above median mean slope within 25km of the city center. If we think that cities build subways when some topographical constraint on their development begins to bind, then we should expect cities more subject to such topographical constraints to respond differently to changes in subways than other cities. The results in column 2 do not support this intuition. Column 3 replicates column 2, but in place of the average slope, measures topographical constraints with the maximal elevation range within 25km of the city center. Like column 3, the results in column 3 do not suggest that subways affect cities with difficult topography differently than than flatter cities.

In column 4 we interact subway growth with an indicator for above median kilometers of highways in a 25km circle around the city. That the coefficients on the main effect and the interaction are zero suggests that subway growth does not have a differential impact depending on whether the city is serviced by highways. In column 5 we include an interaction between the an indicator for above median traffic congestion and subways. If we think that cities tend to build subways as traffic congestion begins to constrain their growth, then we should see congested and uncongested cities respond differently to subways. Column 5 does not support this intuition.

In column 6 we include an interaction of subways with a capital city indicator. If we think, for example, that capital cities are more likely to be the beneficiary of public expenditure than other cities, then we might expect such spending to have a lower return in capital cities than elsewhere. Column 6 does not support this intuition. In column 7 we interact an indicator of an index of

Table 6: First differences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\Delta\ln(\text{pop}_t)$	$\Delta\ln(\text{pop}_t)$	$\Delta\ln(\text{pop}_t)$	$\Delta\ln(\text{pop}_t)$	$\Delta\ln(\text{pop}_t)$	$\Delta\ln(\text{pop}_t)$	$\Delta\ln(\text{pop}_{50-00})$	$\Delta\ln(\text{Lights}_t)$	$\Delta\ln(\text{pop}_t)$
$\Delta\ln(s_t)$	-0.011**	0.001	-0.002			-0.007		0.024	-0.022*
	(0.004)	(0.003)	(0.003)			(0.005)		(0.015)	(0.012)
$\Delta\ln(s_{50-00})$							-0.060		
							(0.058)		
$\Delta\ln(\text{route km}_t)$				-0.001					
				(0.003)					
$\Delta\ln(\text{subway lines}_t)$					-0.002				
					(0.008)				
$\Delta\ln(\text{Bus ridership}_t)$									0.035
									(0.039)
$\Delta\ln(\text{GDP}pc_t)$			0.201***	0.201***	0.201***	0.222***		0.643***	0.006
			(0.042)	(0.042)	(0.042)	(0.038)		(0.106)	(0.103)
$\Delta\ln(\text{COUNTRY POP}_t)$			0.951***	0.951***	0.949***	0.911***		0.260*	1.222***
			(0.118)	(0.117)	(0.118)	(0.150)		(0.144)	(0.214)
YearXContinent dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep Variable	0.113	0.113	0.111	0.111	0.111	0.110	1.234	0.027	0.057
Mean of subways regressor	0.25	0.25	0.26	0.27	0.10	0.27	0.12	0.36	0.10
SD subways regressor	0.69	0.69	0.71	0.75	0.26	0.72	0.24	0.82	0.38
R-squared	0.00	0.29	0.42	0.42	0.42	0.39	0.40	0.46	0.51
Number of cities	138	138	137	137	137	137	138	137	31
Number of subway cities	138	138	137	137	137	137	138	137	31
Number of periods	12	12	12	12	12	6	1	3	8
Observations	1656	1656	1428	1428	1428	730	138	411	63

Dependent variable: Change in log population of metropolitan area in a 5 year period (except columns 8 and 9).
Sample is subway cities. City-level clustered standard errors in parentheses. Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.
(1)- No controls. (2)- Add year-by-continent dummies (3)- Add change in log gdp and change in log country pop. controls.
(4)- Use change in log route km as main regressor. (5)- Use change in log subway lines as main regressor.
(6)- 10 year panel analysis. (7)- Long difference regression 1950-2000, control for $\Delta\ln(\text{GDP}pc_{50-00})$ and $\Delta\ln(\text{COUNTRY POP}_{50-00})$.
(8)- Dep. var. is change in log mean radiance calibrated lights in a 25km circle around the centroid of the city.
(9)- Control for change in bus ridership.

Table 7: Robustness to confounding dynamics

	(1) $\Delta \ln(\text{pop}_t)$	(2) $\Delta \ln(\text{pop}_t)$	(3) $\Delta^2 \ln(\text{pop}_t)$	(4) $\Delta \ln(\text{pop}_t)$	(5) $\Delta \ln(\text{pop}_t)$	(6) $\Delta \ln(\text{pop}_t)$
$\Delta \ln(s_t)$	-0.006	-0.006		0.018	0.016	0.014
	(0.004)	(0.003)		(0.011)	(0.010)	(0.015)
$\Delta^2 \ln(s_t)$			-0.003			
			(0.002)			
$\Delta \ln(\text{pop}_{t-2})$	0.553^{***}	0.599^{***}		0.545^{***}	0.600^{***}	0.546^{***}
	(0.052)	(0.113)		(0.053)	(0.119)	(0.053)
$\Delta \ln(\text{pop}_{t-3})$		-0.059			-0.068	
		(0.082)			(0.087)	
$\Delta \ln(\text{COUNTRY POP}_t)$	0.465^{***}	0.446^{***}		0.434^{***}	0.415^{***}	0.438^{***}
	(0.058)	(0.045)		(0.061)	(0.049)	(0.061)
$\Delta \ln(\text{GDP}pc_t)$	0.128^{***}	0.124^{***}		0.126^{***}	0.122^{***}	0.126^{***}
	(0.025)	(0.023)		(0.024)	(0.022)	(0.024)
$\Delta^2 \ln(\text{COUNTRY POP}_t)$			0.301^{**}			
			(0.100)			
$\Delta^2 \ln(\text{GDP}pc_t)$			0.067^{**}			
			(0.022)			
YearXContinent dummies	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep Variable	0.098	0.091	-0.010	0.098	0.091	0.098
Mean of subways regressor	0.29	0.31	0.02	0.29	0.31	0.29
SD subways regressor	0.74	0.77	1.01	0.74	0.77	0.74
R-squared	0.61	0.60	0.11	0.59	0.58	0.60
Number of cities	137	137	137	137	137	137
Number of subway cities	137	137	137	137	137	137
Number of periods	10	9	11	10	9	10
F-stat excluded instrument				132.36	147.51	153.49
Observations	1235	1124	1291	1235	1124	1235

Dependent variable: Change in log population of metropolitan area in a 5 year period. Sample is subway cities.
City-level clustered standard errors in parentheses. Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.
(1)- First differences controlling for $\Delta \ln(\text{pop}_{t-2})$.
(2)- First differences controlling for $\Delta \ln(\text{pop}_{t-2})$ and $\Delta \ln(\text{pop}_{t-3})$.
(3)- Second differences regression.
(4)- Instrument $\Delta \ln(s_t)$ with $\ln(s_{t-4})$ controlling for $\Delta \ln(\text{pop}_{t-2})$.
(5)- Instrument $\Delta \ln(s_t)$ with $\ln(s_{t-4})$ controlling for $\Delta \ln(\text{pop}_{t-2})$ and $\Delta \ln(\text{pop}_{t-3})$.
(6)- Instrument $\Delta \ln(s_t)$ with $\ln(s_{t-8})$ controlling for $\Delta \ln(\text{pop}_{t-2})$.

Table 8: First Differences - Distributed Lag Models

	(1) $\Delta\ln(\text{pop}_t)$	(2) $\Delta\ln(\text{pop}_t)$	(3) $\Delta\ln(\text{pop}_t)$	(4) $\Delta\ln(\text{pop}_t)$	(5) $\Delta\ln(\text{pop}_t)$
$\Delta\ln(s_t)$	-0.002				-0.002
	(0.003)				(0.004)
$\Delta\ln(s_{t-1})$		-0.002			-0.002
		(0.003)			(0.003)
$\Delta\ln(s_{t-2})$			-0.003		-0.003
			(0.003)		(0.003)
$\Delta\ln(s_{t-3})$				-0.005	-0.006
				(0.003)	(0.004)
$\Delta\ln(\text{GDP}pc_t)$	0.201^{***}	0.201^{***}	0.200^{***}	0.200^{***}	0.200^{***}
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
$\Delta\ln(\text{COUNTRY POP}_t)$	0.951^{***}	0.948^{***}	0.946^{***}	0.945^{***}	0.944^{***}
	(0.118)	(0.119)	(0.119)	(0.119)	(0.118)
YearXContinent dummies	Yes	Yes	Yes	Yes	Yes
Mean of Dep Variable	0.11	0.11	0.11	0.11	0.11
Number of cities	137	137	137	137	137
Number of subway cities	137	137	137	137	137
Number of periods	12	12	12	12	12
Observations	1428	1428	1428	1428	1428

Dependent variable: Change in log population in a 5 year period.
Sample is cities with subway in 2010. City-level clustered standard errors in parentheses.
Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.

Table 9: Robustness to confounding unobservables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$\Delta \ln(s_t)$	-0.002	-0.001	-0.004	0.002	0.003	-0.000	-0.003	-0.029	-0.006	-0.000	-0.000	0.005	-0.002
	(0.003)	(0.006)	(0.005)	(0.007)	(0.004)	(0.004)	(0.006)	(0.032)	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)
(25 km slope > median) $\times \Delta \ln(s_t)$		-0.000											
		(0.006)											
(25 km elevation range > median) $\times \Delta \ln(s_t)$			0.005										
			(0.006)										
(25km highways > median) $\times \Delta \ln(s_t)$				-0.004									
				(0.008)									
(TomTom congestion > median) $\times \Delta \ln(s_t)$					-0.012								
					(0.008)								
Capital $\times \Delta \ln(s_t)$						-0.004							
						(0.006)							
Good doing business $\times \Delta \ln(s_t)$							0.003						
							(0.009)						
System built post WW II $\times \Delta \ln(s_t)$								0.028					
								(0.031)					
(Centralized > median) $\times \Delta \ln(s_t)$									0.011*				
									(0.006)				
(Subway coverage > median) $\times \Delta \ln(s_t)$										-0.002			
										(0.004)			
(City pop. 1950 > median) $\times \Delta \ln(s_t)$											-0.003		
											(0.007)		
Coastal city $\times \Delta \ln \ln(s_t)$												-0.015**	
												(0.006)	
(Bus ridership pc > median) $\times \Delta \ln(s_t)$													0.002
													(0.007)
$\Delta \ln(\text{GDP}pc_t)$	0.201***	0.201***	0.201***	0.201***	0.299***	0.201***	0.195**	0.202***	0.202***	0.201***	0.201***	0.203***	0.082
	(0.042)	(0.042)	(0.042)	(0.042)	(0.080)	(0.042)	(0.066)	(0.043)	(0.042)	(0.042)	(0.042)	(0.042)	(0.061)
$\Delta \ln(\text{COUNTRY POP}_t)$	0.951***	0.951***	0.955***	0.952***	0.807***	0.952***	0.749***	0.947***	0.939***	0.947***	0.949***	0.956***	0.840**
	(0.118)	(0.117)	(0.115)	(0.117)	(0.111)	(0.119)	(0.092)	(0.117)	(0.119)	(0.117)	(0.117)	(0.109)	(0.366)
Year $\times$ Continent dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep Variable	0.11	0.11	0.11	0.11	0.10	0.11	0.15	0.11	0.11	0.11	0.11	0.11	0.10
Number of cities	137	136	136	137	84	137	63	137	137	137	137	137	40
Number of subway cities	137	136	136	137	84	137	63	137	137	137	137	137	40
Number of periods	12	12	12	12	12	12	12	12	12	12	12	12	12
Observations	1428	1416	1416	1428	937	1428	579	1428	1428	1428	1428	1428	453

Dependent variable: Change in log population in a 5 year period. Sample is subway cities in 2010. City-level clustered standard errors in parentheses.
Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.

institutional quality with subways. If we think that a city's response to subways depends on its ability to reorganize private sector employment, then we might expect cities with a low score on this index to respond differently to subways than those with a high score. The data also do not support this idea.

In column 8 we interact subways with an indicator for whether the subway system predates the second world war — the point at which cars became ubiquitous as a transportation mode. If we think that older cities are laid out in a way that is more conducive to public transit, then we might expect to see such older cities respond differently to subways than other cities; we do not. In column 9 we interact subways with an indicator for whether the city is above the sample median in the centralization of its light in 2010.[20] These estimates provide weak evidence for a very small difference in the way centralized and decentralized cities respond to subways.

Column 10 investigates whether the subway network configuration is important. To accomplish this, we calculate the share of all light within 25k of the center that is within 1500m of a station. If cities respond differently to subways that serve a larger fraction of their economic activity and population, then we should expect to see a significant coefficient on the interaction of this variable with subways. Our data do not support this intuition. Column 11 investigates whether cities that were large in 1950 respond differently to subways. They do not. In column 12 we see that coastal cities grow slightly less fast in response to subways than do other cities, but this effect is tiny.

Finally, in column 13 we ask whether cities with an effective bus network respond differently to subways than those that do not. The data suggest that they do not. This is consistent with the first difference regression in column 9 of table 6, where we see that controlling for bus ridership in a first difference regression does not lead to a positive estimated effect of subways.

Discussion We have presented four types of results, cross-sectional, first difference, IV and second difference. Consistent with descriptive evidence presented in section 1, cross-sectional estimates are much larger than first differences estimates. Results based on metropolitan area light intensity are qualitatively similar to those based on population. Once we add continent specific year effects in column 3 of table 6, the cross-sectional estimate of the effect of doubling subway stations is a 26% increase in population. In first differences, the corresponding estimate is less than 1% and is indistinguishable from zero. Our attempts to deal with confounding dynamics and with omitted variables do not change this conclusion.

Broadly, formal econometric results support the conclusion suggested by the descriptive evidence. That is, that big cities build subways and that these subways subsequently have little or no effect on the population in these cities. Our most favorable IV regressions indicate that doubling a subway system will increase population by less than 2%, although these estimates are never

[20]Our index of centralization is calculated by taking the ratio of mean light within 25k of the center to all light within 50km of the center.

distinguishable from zero and most estimates of the effect of subways on population are much smaller.

7. Subways and urban form

In this section, we use the lights data to investigate the relationship between urban centralization and subway extent. Given that the resolution of the radiance calibrated lights data we use is about 1km square, this is small enough to provide information about the way that cities are laid out, and inspection of figure 2 shows that the lights data reflect broad patterns of urban density.

Following a long tradition in urban economics, we characterize the centralization of each with a density gradient (e.g., Clark, 1951; Mills and Peng 1980). In our case, we estimate a light intensity gradient for every city-year to measure the rate at which density decays with distance from the center. To do this, we first we calculate mean light intensity, for disks with radius, 1.5k, 5k,10k 25km and 50k, around each city's centroid. These disks describe a series of donuts surrounding the center of each city. Let $x_i \in \{0.75\text{km}, 3.25\text{km}, 7.5\text{km}, 17.5\text{km}, 37.5\text{km}\}$ be the radii of the circles lying halfway between the inner and outer border of these donuts. For example, $x_i = 3.25$ lies halfway between the inner and outer radius of the donut that extends from 1500m to 5k from a city's center. For each such donut, let y_i denote the average light intensity in the donut. All together, for each city, we now have 5 pairs of light intensity and distance, (y_i, x_i).

To characterize the centrality of each city, we estimate the following regression

$$\ln y_i = A + B \ln x_i + \epsilon_i.$$

The coefficient B in this regression is the rate at which light decays with a change in distance from the center, and will be our measure of centrality for each city. All else equal, a city with a more negative value of B sees its density decline more quickly with distance from the center, and is therefore, 'more centralized'.

We are interested in determining if the light gradient changes with subway expansions, and follow our previous empirical approach but now using the light gradient in a city-year as our dependent variable. That is, we regress our estimate of B for each city on a measure of subways using the various regression specifications employed to analyze subways and population.

Table 10 reports our results. Column 1 shows the pooled OLS estimate. In the cross section, the elasticity of light gradient to subway extent is 0.034. Given that the light gradient is negative, this indicates that cities with larger subway systems have a flatter light gradient and are less centralized. Column 2 presents the first difference regression result in which we find an elasticity estimate of 0.023. In column 3 we control for the second lag of population growth, and find virtually the same coefficient as in column 2. Columns 4 and 5 present our instrumented first difference estimates and show that we find a statistically significant elasticity of 0.060. The finding that subways cause decentralization is quite robust; we obtained a similar result when analyzing the ratio of light in the downtown to the periphery or the changes in light in each ring. The data clearly point to the same conclusion: subways make the city light gradient flatter.

Table 10: Decentralization - Radiance calibrated light gradient

	(1) OLS	(2) OLS-FD	(3) OLS-FD	(4) 2SLS-FD	(5) 2SLS-FD
$\Delta \ln(s_t)$		0.023***	0.024***	0.047*	0.060**
		(0.0062)	(0.0062)	(0.025)	(0.024)
$\ln(s_t)$	0.034***				
	(0.010)				
$\Delta \ln(\text{GDP}pc_t)$		-0.078	-0.079	-0.100*	-0.11*
		(0.053)	(0.053)	(0.056)	(0.058)
$\Delta \ln(\text{COUNTRY POP}_t)$		-0.0051	-0.0014	-0.091	-0.13
		(0.17)	(0.17)	(0.21)	(0.22)
$\ln(\text{GDP}pc_t)$	0.043*				
	(0.024)				
$\ln(\text{COUNTRY POP}_t)$	0.048***				
	(0.014)				
$\ln(\text{pop}_{t-2})$			0.0049		0.0072
			(0.0051)		(0.0049)
Geographic controls	Yes	Yes	Yes	Yes	Yes
YearXContinent dummies	Yes	Yes	Yes	Yes	Yes
Mean of Dep Variable	-0.811	0.041	0.041	0.041	0.041
Mean of subways regressor	3.06	0.36	0.36	0.36	0.36
SD subways regressor	1.49	0.82	0.82	0.82	0.82
R-squared	0.35	0.19	0.19	0.17	0.15
Number of cities	137	137	137	137	137
Number of subway cities	137	137	137	137	137
Number of periods	4	3	3	3	3
Observations	548	411	411	411	411

Col. 1 dependent variable is the slope of the light gradient in a city-year period. For each city-year, a linear regression was estimated between the log mean radiance calibrated light intensity in rings of 1.5km, 5km, 10km, 25km and 50km and log distance from from the city center. centroid. Columns 2-5 use as dependent variable the change in slope over a 5 year period.
City-level robust standard errors in parentheses.
Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.

These results contradict the conventional wisdom that subways lead to a concentration of activity in the downtown core, and at first glance, this may seem surprising. In fact, almost any theoretical model of the spatial organization of a city will predict that the city spreads out as transportation costs fall. This is exactly what our data show. Our results are also consistent with Baum-Snow (2007), who finds that radial highways cause US cities to decentralize, and with Ahlfeldt and Wendland (2011) who find that commuter rail contributes to the decentralization of Berlin.

8. Ridership

In this section we turn to the question of what subway expansions do to overall public transit system ridership, an issue of first order importance for public transit planning and financing. In addition, because we collected data on public transit ridership distinguishing between subway and bus ridership, we can also speak to the substitution between the two modes of transport.

Previous literature has provided wide-ranging predictions about substitution patterns. For example, the Los Angeles subway expansion was opposed by groups representing residents of poor neighborhoods under the argument that funding (and hence the supply) of buses serving these neighborhoods would decrease as a consequence of the large operating subsidies the subway would necessitate. If this argument holds in general, we should observe that bus ridership decreases when cities engage in subway expansions. On the other hand, other authors have argued that overall public transit ridership should be positively affected by subway expansions since buses and subways complement each other in providing public transportation. As an example of why this would occur they point out that bus lines are redesigned after subway expansions to feed passengers into the subway system. Under this argument bus ridership should increase when subway systems expand. Finally, case studies of subway expansions have argued that since most subway users were previously bus users, the net effect on overall ridership of subway expansions should be around zero.

Table 11 shows pooled cross sectional estimates relating subway size to ridership. Consistent with casual observation, the table shows that cities with larger subway systems have larger system ridership (the elasticity is 0.90 in column 2). Similarly, cities with larger subway systems have more subway riders (the elasticity in column 4 is 1.19) as well as bus riders (the elasticity in column 6 is 0.61). As with Table 5, we vied these pooled OLS estimates as mainly descriptive.

Table 12 presents our first difference estimations. In Column 3 we find that the public transit ridership elasticity to subway extent is 0.68 (significant at the 5% level). This positive elasticity estimate contradicts the hypothesis that expanding subway systems does not lead to increases in public transit ridership.

In columns 4-6 we show that subway ridership elasticity to subway extent is 0.61 (significant at the 5% level). On the other hand, the effect of subway expansions on bus ridership is found to be close to zero in columns 7-9. Our interpretation of these results is that there is no net substitution of subways for buses in the face of subway expansions. Overall, subway expansions lead to increased public transit ridership, and this is all coming from increased use of the subway system. This result echoes previous findings that more highway kilometers in a city lead to increased driving as in Duranton and Turner (2011).

Table 11: Log ridership - Pooled cross section

	ln(All ridership$_t$)		ln(Subway ridership$_t$)			ln(Bus ridership$_t$)
	(1)	(2)	(3)	(4)	(5)	(6)
ln(s_t)	0.66***	0.90***	1.09***	1.19***	0.54***	0.61***
	(0.16)	(0.15)	(0.13)	(0.15)	(0.14)	(0.11)
ln(GDPpc_t)		-1.31***		-0.25		-1.76***
		(0.31)		(0.28)		(0.37)
ln(country pop$_t$)		-0.12		-0.09		-0.04
		(0.17)		(0.15)		(0.15)
Geographic controls	No	Yes	No	Yes	No	Yes
YearXContinent dummies	No	Yes	No	Yes	No	Yes
Mean of Dep Variable	19.77	19.77	18.82	18.82	18.60	18.60
Mean of subways regressor	4.04	4.04	3.87	3.87	3.67	3.67
SD subways regressor	0.98	0.98	1.04	1.04	1.17	1.17
R-squared	0.32	0.78	0.57	0.74	0.23	0.70
Number of cities	34	34	78	78	45	45
Number of subway cities	34	34	78	78	45	45
Number of periods	10	10	10	10	10	10
Observations	88	88	225	225	117	117

Dependent variable: Log ridership of subways and buses in metropolitan area in period t.
City-level clustered standard errors in parentheses. Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.
Geographic controls are capital city dummy, log km to ocean, log km to land border, and log km to major navigable river.
(1)-Pooled cross section. (2)-Add geographic controls, GDP pc control, country population, and yearXcontinent dummies.

Table 12: Log ridership - First differences

	$\Delta \ln(\text{All ridership}_t)$			$\Delta \ln(\text{Subway ridership}_t)$			$\Delta \ln(\text{Bus ridership}_t)$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \ln(s_t)$	0.728**	0.734**	0.678**	0.572**	0.660**	0.613**	-0.001	0.005	-0.011
	(0.238)	(0.261)	(0.299)	(0.213)	(0.198)	(0.224)	(0.044)	(0.060)	(0.050)
$\Delta \ln(\text{GDP}pc_t)$			0.069			0.158			0.271
			(0.229)			(0.228)			(0.276)
$\Delta \ln(\text{COUNTRY POP}_t)$			1.238			1.116			3.181**
			(1.302)			(1.154)			(1.186)
YearXContinent dummies	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Continent dummies	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Mean of Dep Variable	0.064	0.064	0.064	0.150	0.150	0.150	0.014	0.014	0.014
Mean of subways regressor	0.06	0.06	0.06	0.11	0.11	0.11	0.10	0.10	0.10
SD subways regressor	0.15	0.15	0.15	0.23	0.23	0.23	0.38	0.38	0.38
R-squared	0.39	0.56	0.57	0.20	0.41	0.42	0.00	0.35	0.39
Number of cities	24	24	24	63	63	63	31	31	31
Number of subway cities	24	24	24	63	63	63	31	31	31
Number of periods	8	8	8	9	9	9	8	8	8
Observations	48	48	48	143	143	143	63	63	63

Dependent variable: Change in log ridersip of metropolitan area in a 5 year period. Sample is subway cities.
City-level clustered standard errors in parentheses. Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.
(1)- No controls. (2)-Add yearXcontinent dummies (3)-Add log gdp and log country pop. controls.

9. Conclusion

On the basis of figure 3, it is natural to conjecture that some sort of subway system is essential to the growth of cities beyond 5m in the rich world and that a subway system is also important to the growth of cities in the developing world.

A back of the envelope calculation also suggests that subways could have dramatic effects on the population of a city. Ten car trains can carry about 35,000 people per hour,[21] or almost 90,000 over the course of a 2.5 hour morning commute. This means that a single subway line could allow an extra 90,000 people to get to work in a central city. With a 50% labor force participation rate this leads to a population increase of 180,000. In our sample, population for a mean subway city in 2010 is about 4.7m, so this is almost a 4% population increase. Since an average subway system has 5.4 lines, adding a single line is a 19% increase. Dividing, this suggests that a theoretical upper bound for the subway elasticity of population of about 0.2. If we consider only the technical capabilities of subways, the notion that they could have an important effect on urban growth is defensible.

Our cross-sectional estimate of the effect a subway line is about twice as large as the calculation above suggests (table 5 column 5). That is, the cross-sectional estimates of the effects of subways on population are large relative to what we might reasonably guess on the basis of the physical capabilities of subways. Purely on a priori grounds, this raises the suspicion that big cities cause subways and not the converse. This suspicion finds support in our other estimates. Our first difference estimates suggest that doubling the extent of a subway network causes a tiny increase in population. While these estimates vary somewhat with technique, all are dramatically smaller than cross sectional estimates, and those we prefer are close to 1%.

To investigate the possibility that subway expansions systematically occur in years with low growth, we also conduct second difference and instrumental variables estimates. These estimates also yield tiny elasticities that are not statistically distinguishable from zero. Thus, the weight of evidence suggests that big cities build subways, but that subways have at most a tiny effect on urban population growth, a conclusion consistent with patterns visible in the raw data. We suspect that the similarity between instrumental variables and first differences estimates reflects the fact that, in our world sample, there is sufficient cross-country heterogeneity in the political economy of subway construction that this process is approximately random in our sample after we control for city specific effects.

While a more exhaustive analysis of the implications of subways for urban form is a subject for further research, our analysis begins this investigation. We find evidence that subways allow the central cores of large cities to spread out. This decentralization accords with the predictions of canonical theoretical models of cities: when transportation costs fall, economic activity spreads

[21] Transit Capacity and Quality of Service Manual (1999)(ch. 1, part 1, p1-22), Transit Cooperative Research Program, 2101 Constitution Ave. N.W., Washington, D.C. 20418

out. It is also consistent with previous analyses of the effects of radial highways on urban form. These studies also conclude that cities spread out in response to reductions in transportation costs.

It is natural to ask why the realized effects of subways on urban population diverge so dramatically from the technical frontier. Our results reflect the effects of subways that are actually built rather than their theoretical capabilities. Thus, a natural conjecture is that subways do not have much effect on city population because the subways that are actually built are not used at their full capacity. Baum-Snow and Kahn (2005) find evidence consistent with this hypothesis for the US. If true, this suggests that our results reflect a systematic failure to build useful subway systems rather than an intrinsic failure of subways to be useful. For example, our data indicate that subways are, overwhelmingly, a central city phenomenon so only people living within a few kilometers of the center can reasonably expect to walk to a station. On the other hand, much urban growth occurs on the edges of cities, e.g., Burchfield, Overman, Puga, and Turner (2006), thus subways may simply not service the areas where substantial population growth is more likely to take place. Alternatively, we know from Gordon and Willson (1984) that population density and income are good predictors of ridership. So it may be that subways are located in places where people want to live, but not where they want to ride subways.

A second conjecture also suggests itself. Consistent with within city evidence, e.g., Billings (2011) and Gibbons and Machin (2005), we find that subways reorganize activity in cities, even though they do not increase it. This suggests that an average subway is heavily used, as in our theoretical example, but rather than allowing more people to move to the city, this extra transportation capacity is used primarily to allow more travel by incumbent residents of the city. If true, this would be broadly consistent with results in Duranton and Turner (2011) on the effects of highways on travel behavior in US cities. That is, that most of the new travel caused by new highways is increased travel by incumbents. Although it is beyond the scope of the present investigation, developing a better understanding of why the observed effects of subways are so much smaller than we might predict on the basis of their physical characteristics seems like an obvious area for further research.

Many of our first difference estimates, while small, are not zero. This leads to the question of whether the effects of subways are big enough to justify a construction subsidy. To develop some intuition around this question, we suppose that a 10 percent increase in the extent of a subway system causes about a 0.1 percent increase in population. This is slightly larger than the largest of our preferred first difference estimates. It is well known that productivity increases with city size, and it is probably uncontroversial to say that city productivity increases by less than 5 percent when city size doubles. On the basis of these constants, an upper bound on the effect of a 10 percent increase in the extent of a city's subway network on aggregate city economic activity would be $0.05 \times [0.01 \times 0.1] \times 100 = 0.005\%$. Using our data on GDP and cost estimates from Baum-Snow and Kahn (2005) we can compare the value of this flow of income with the capital cost of construction. Using parameter values favorable to subway construction this calculation suggests that for an average city in our sample the value of economic activity created by subway expansion is equal to about twenty percent of the cost of construction, although the ratio of increased land rent to cost is dramatically smaller.[22] These estimates are smaller still if subways have no effect on population levels at all.

Our finding that subways have little or no effect on population growth does not seem consistent with the claims for their transformative effects sometimes made by proponents of subway construction. If subway systems have the abilities their advocates ascribe to them, then we should expect them to make cities more attractive to immigrants and hence to create population growth. Our data, therefore, broadly contradict these claims, and with them much of the justification for construction and operating subsidies. With this said, our finding does not mean that subway construction is bad public policy. Rather it suggests that the evaluation of subway projects ought to rest on the demand for mobility, farebox revenue, and not on the ability of subways to promote city growth.

[22]Calculations available on request.

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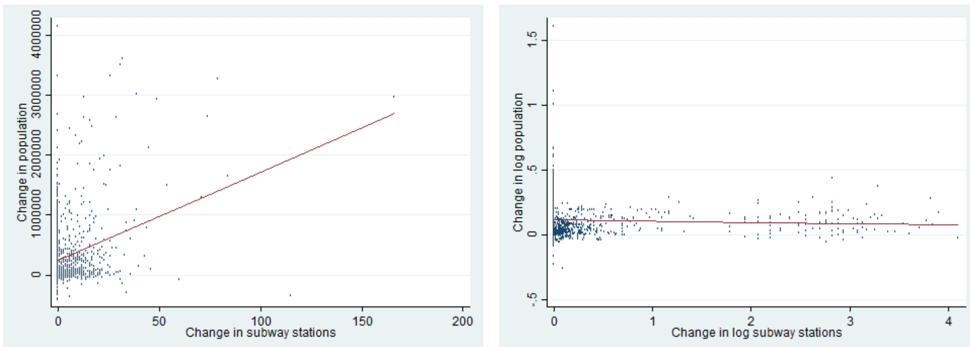
Appendix

Figure A.1: Levels versus logarithmic specification

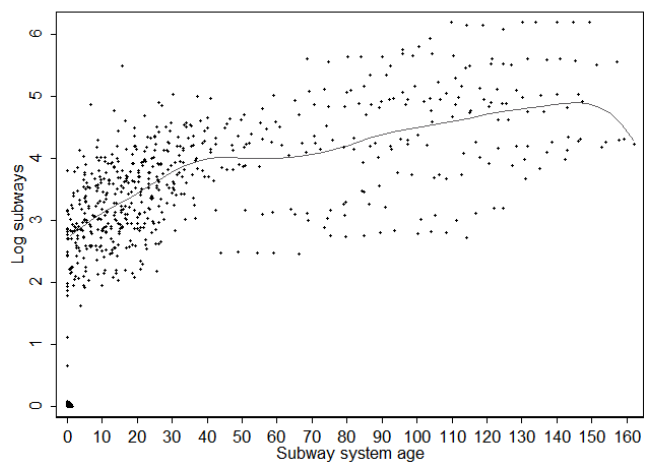


(a) Levels (b) Logarithms

First stage results

Where figure A.2 shows the growth of the world's subways, figure A.2 traces out the size of individual systems as a function of the time since they opened. Each marker in this figure describes a city year, so that there is one marker for each of the city-years in our data where at least one subway station is open. Consistent with figure A.2, most of the observations are in the left portion of the graph. This reflects the fact that many subways systems have opened in the past 30 years. On the other hand, markers in the right hand portion of the graph describe the handful of subway systems that date back to the 19th century. The solid line in the figure describes a locally weighted regression of system size on system age. This figure suggests that the expansion of a city's subway network is predictable. Expansion is rapid and approximately loglinear during the first 30-40 years after a system opens. After a system is about 40 years old, growth slows but remains approximately log linear, though at a lower growth rate.

Figure A.2: Stations in a subway system by time since system opening



Note: Vertical axis is log of operation stations in a system. Horizontal axis is years since station opening. Dots indicate individual city-years.

Table A.1: Subways first stage: First difference – lagged subway instruments

	(1)	(2)	(3)
	$\Delta \ln(s_t)$	$\Delta \ln(s_t)$	$\Delta \ln(s_t)$
$\ln(s_{t-4})$	-0.094***	-0.100***	
	(0.008)	(0.008)	
$\ln(s_{t-8})$			-0.067***
			(0.005)
$\Delta \ln(\text{pop}_{t-2})$	0.084	-0.121	0.199
	(0.151)	(0.526)	(0.151)
$\Delta \ln(\text{pop}_{t-3})$		0.251	
		(0.585)	
$\Delta \ln(\text{GDP}pc_t)$	0.024	0.001	0.057
	(0.160)	(0.170)	(0.167)
$\Delta \ln(\text{COUNTRY POP}_t)$	0.905	0.980	1.156*
	(0.660)	(0.662)	(0.613)
YearXContinent dummies	Yes	Yes	Yes
Mean of Dep Variable	0.29	0.31	0.29
R-squared	0.13	0.12	0.10
Number of cities	137	137	137
Number of subway cities	137	137	137
Number of periods	10	9	10
Excluded instruments F-stat	132.36	147.51	153.49
Observations	1235	1124	1235

Dependent variable: Change in log subway stations in a 5 year period.
Stars denote significance levels: * 0.10, ** 0.05, *** 0.01.
Sample is subway cities.
City-level clustered standard errors in parentheses.

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