ABSTRACT

Essays on Transportation: Considering Multiple Modes and Land Use Interactions

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This dissertation provides three examples of how considering interactions across transport modes as well as land use systems is important for addressing the biggest challenges in sustainable development, particularly climate change and growing inequality. In the first essay, I explore path dependency in urban form for U.S. cities built around rail transit prior to the automobile. I find that these cities continue to be denser and have lower per capita transportation emissions than cities that came of age after the automobile. I estimate the size of the effect and how long it lasts. The built environment is durable, and urban infrastructure is costly to alter post-construction, so land use and transport decisions made early in a city’s history can have a lasting environmental impact. The second essay exploits a natural experiment to quantify the impact of bikesharing on bus transit ridership in New York City. This work demonstrates one way in which shared modes impact pre-existing public transit systems, which is particularly important as these systems are expanding and operating outside of traditional public agencies. The way these modes work together determines the overall quality of the transport network. The third essay discusses the concept of accessibility and how accessibility measures can be used in the case of Nairobi to explore the dynamics of social exclusion across modes, residential location, and income. This dissertation provides three examples of how sustainability goals may fall short if transportation is not viewed as a multimodal system that interacts with and shapes urban form.
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Introduction

Transportation planning has long considered the interactions across transport modes as well as land use systems. This dissertation provides three examples of how considering these interactions is important for addressing the biggest challenges in sustainable development. As Schaeffer and Sclar, (1980) write, ”Cities exist as a spatial solution to the problem of improving contact or access among people”. On the most basic level cities develop out of the need to reduce distances. If that is fundamental to the existence of the city, how do our transportation and land use systems determine how sustainable the city is? The most pressing challenges today are reducing greenhouse gas emissions and reversing growing economic inequality. This dissertation provides three different examples of how transportation policies that overlook the interaction with land use and impacts across modes will likely fall short of sustainability goals.

In the first chapter, I study the relationship between historical transportation infrastructure and carbon dioxide emissions in U.S. cities. While fixed rail transit tended to encourage density along rail lines, the introduction of the automobile led to sprawling American cities. The central empirical approach in this chapter is to examine the significance of historical data in explaining modern density and transportation emissions. I use the Schaeffer-Sclar Tracked City Framework to describe the particular urban form that
developed around rail transit prior to the automobile. Using both regression and matching analyses, I compare cities based on how many miles of rail were built prior to the widespread use of the automobile. The regression analysis shows that cities with more miles of rail in 1907 are denser today and have lower per capita emissions in the transportation sector across the entire metropolitan region. There are substantial benefits for cities that invested most heavily in rail. Because it is difficult to separate the effect of rail transit from historical density, I also test the results using matching and find that rail transit is likely to account for at least a medium-term impact on density. While the possible simultaneity between transportation and density deserves further study, the results indicate that urban form can persist and that this may have long-term environmental impacts.

In the second chapter, I quantify the impact that bikesharing has on bus transit ridership by exploiting a natural experiment in New York City. Because the bikesharing system was rolled out in phases to different areas of the city, I use a difference-in-differences identification strategy to separate bus routes into control and treatment groups. I also develop ways to quantify the treatment intensity of bikesharing. I find a significant decrease in bus ridership on treated routes compared to control routes that coincides with the opening of the bikesharing system. This indicates that either a large proportion of bikeshare members are substituting away from bus transit or that bikesharing may have impacted the travel behavior of non-members. This research supports other findings that bikesharing may not have large environmental benefits. It also brings up bigger questions about how bikesharing can be integrated with preexisting modes and if it should be treated as a private system or as part of the larger public transit network.
These ideas come together in the third chapter, where I use accessibility measures to quantify the relationship across transport modes and land uses. The goal of transportation is rarely to travel for the sake of travel; instead, it is to gain access to opportunities, which inherently is a function of both the transport and land use systems. In low income countries in Africa, Asia, and Latin America where data are limited or unavailable, there are few empirical studies looking at the concept of accessibility and even fewer that incorporate semi-formal bus systems, also called paratransit. In this work, I use a cumulative opportunities measure on a new dataset on Nairobi’s bus and matatu system to map and quantify accessibility in Nairobi for driving, paratransit, and walking, and determine if accessibility differs across modes or residential typologies based on income. This work raises important questions about whom the city is being built for, and how inequality is reflected in the city’s infrastructure, particularly when investments have emphasized highway building over pedestrian improvements.

The focus of accessibility planning is on understanding how well transport systems enable people to reach urban opportunities and represents a shift from how we currently plan and talk about transportation (Sclar and Lönnroth, 2014; UN Habitat, 2013). I demonstrate that accessibility metrics can be useful for quantifying and visualizing the multi-modal nature of transport networks and for capturing the way transport and land use interact to provide urban populations with access to opportunities. Increased accessibility as the main goal of transportation planning is a useful tool to both understand the unintended impacts across modes and between transport and land use systems and a way to develop transportation policies that meet sustainability goals.
1.1 Introduction

The transportation sector accounts for roughly one-third of carbon dioxide emissions in the U.S., more than any other end-use sector (U.S. Energy Information Administration, 2011). Transit-oriented development is an urban planning strategy that is used to address emissions by decreasing vehicle miles traveled, among other apparent benefits (Cervero et al., 2004). Transit-oriented development generally refers to building at high density around public transit stations while supporting mixed-use and non-motorized travel. Although this kind of urban development may be an expensive strategy to pursue, it could have long-term impacts that are harder to reverse. Taking a historical perspective, this paper explores if cities that were built around rail transit, prior to the widespread use of the automobile, are denser today and if the miles of rail transit built historically explains variation in per capita carbon dioxide emissions across cities. It explores how long this effect may last and its magnitude.

Because they are population centers, cities have large aggregate CO₂ emissions from transportation, but lower per capita emissions than their rural counterparts. This relationship tends to hold true, but there is significant variation in emissions across cities. Much
work has gone into understanding this variation, including a large literature on how urban
form influences vehicle miles traveled (VMT), which in turn impacts emissions (Bento et
al., 2005; Brownstone and Golob, 2009; Fang, 2008; Heres-Del-Valle and Niemeier, 2011).
A meta-analysis (Ewing and Cervero, 2010) and more recent meta-regression analysis
(Stevens, 2016) on the relationship between compact development and VMT find that
compactness is associated with reduced driving, but these studies differ in their interpre-
tation of how large the effect is (Ewing and Cervero, 2017) and they do not address the
variation in the long-term implications of design. Salon et al., (2012) review the empirical
evidence on the effectiveness of different strategies in reducing VMT. They find that land
use factors, such as increasing density, tend to have a relatively small effect compared to
other potential policies, but note that these factors may have an impact over longer-time
periods, or a larger combined effect or threshold effect when multiple land use factors are
changed (Bento et al., 2005; Boarnet et al., 2011a; Boarnet et al., 2011b; Ewing, Pendall,
and Chen, 2002; Hamidi et al., 2015; Salon, 2009). Using a number of ways of measuring
urban form, Bento et al., (2005) find that the probability of driving is lower if a city is more
centralized, if it has more rail miles, or if the road density is lower. The individual effect
from changing any one of their measures of urban form or transit supply is modest, but
they show large effects when these measures are considered jointly. One example they
use is if households were to live in a city with characteristics identical to Boston, their
vehicle miles traveled would be 25% lower than if they lived in a city with characteristics
like Atlanta. But how Boston and Atlanta came to be that way is left unexplained.

These characteristics of urban form that impact VMT and emissions may be the result
of a variety of historical decisions and events. In particular, transportation technologies
have shaped cities over time. Fixed rail transit tended to encourage density, but the introduction of the automobile and the interstate highway system led to a sprawling out of American cities. The goal of this research is to understand if the urban form that’s characteristic of cities that came of age prior to the automobile, is related to the variation in density and per capita transportation emissions across U.S. cities, how long the relationship lasts, and what its magnitude is.

I use the Schaeffer-Sclar Tracked City framework as a way to describe the particular urban form that developed around rail transit prior to the growth of the automobile. The central empirical approach is to examine the significance of historical data in explaining modern density and transportation emissions. Through a series of regressions I find a significant relationship between the miles of rail transit built in 1907 and central city density in 2000, and between miles of rail and per capita carbon dioxide emissions in 2002. In other words, Tracked Cities, cities that came of age prior to the automobile, continue to be denser and have lower emissions today. For cities that invested heavily in rail the benefits are relatively large. Because it is difficult to separate the effect of rail transit from other agglomeration forces, I also test the results using a matching specification. Matching is a quasi-experimental technique that I use to control for baseline characteristics, particularly historical density. I find that the effect of the Tracked City is significant in the medium-term (more than 60 years later), but that density is a more important determinant in the longer-term relationship. This work adds to the literature by showing the time horizons over which urban density lasts and by giving a point estimate of the size of the effect. Implications and limitations of this analysis are discussed further.
1.2 Prior Research on Path Dependency in Cities

There is a growing body of empirical work studying the impact of history on cities across a variety of characteristics. A portion of this literature exploits different historical shocks and finds that city size and location tend to persist in spite of negative shocks (Bosker et al., 2008; Davis and Weinstein, 2002) and that historical circumstances help to explain variation in population, urban location, and economic activity (Ahlfeldt et al., 2015; Hanlon, 2017; Michaels and Rauch, 2016). Other papers explore how historical factors that are now obsolete continue to shape cities. For example, Bleakley and Lin, (2012) look at portage cities in the U.S., locations where, centuries ago, trade goods had to be hauled over land because of major river obstacles. Settlements formed at these locations because they offered an economic advantage of eliminating the need to port goods. Comparing portage cities to cities that were similarly dense at the time, they find that portage cities persist and in fact continue to grow even though their initial natural advantage is obsolete. Another study focuses specifically on the effect of railroads. Jedwab and Moradi, (2016) find that colonial railroads in Ghana had a strong effect on urban population growth, that this has had long-term impacts on the urbanization rate, and is associated with better infrastructure today.

In addition, there is evidence at the neighborhood-level that streetcar infrastructure continues to impact density. Brooks and Lutz, (2016) find that areas near streetcar stops in Los Angeles are denser today in terms of population and buildings than comparable areas and test a number of potential mechanisms that could explain this relationship. They conclude that durable capital plays a limited role but that zoning and agglomeration, two
mutually reinforcing factors, likely account for the persistent density in these locations. Similarly, Block-Schachter, (2012) shows that neighborhoods in Boston that were closer to streetcar lines were denser than areas built further away and that they continue to be denser in 2000 even though there are no longer streetcars. He shows that the co-development of rail and land use in the past shapes neighborhood-scale urban form and continues to influence travel behavior.

There are two other notable studies on the determinants of urban density in U.S. cities. First, Baum-Snow, (2007) find that the construction of the U.S. interstate highway system caused a significant decline in central city population between 1950 and 1990. Although not focused specifically on permanence or persistence, these findings demonstrate the effect of transportation infrastructure on population density over long time periods in U.S. cities. Finally, in perhaps the most relevant paper, Burchfield et al., (2006) study the factors that effect how scattered or compact residential development is using a sprawl index. One of the potential factors they test is the number of streetcar passengers per capita in 1902. They find that a one-standard deviation increase in historical streetcar usage significantly decreases their sprawl index. In other words, whether the city center was shaped before the automobile is a significant predictor of compactness.

Both at the inter-city and intra-city scale, there is an emerging literature on the importance of path dependence in explaining modern urban characteristics (Bleakley and Lin, 2015), and some evidence that historical transportation technology is a factor. First, by focusing on modern density, I add empirical evidence of the role that history plays in shaping urban form, not just urban location or size. Second, I extend the work by Block-Schachter, (2012) and Brooks and Lutz, (2016) from the neighborhood-level density
to a make a cross-sectional comparison of the impact of historical rail transit across U.S. cities. Third, I use the Schaeffer-Sclar Tracked City framework, described in the following section, to put the co-development of land use and transportation into historical context and to quantify a particular type of urban form. Finally, I extend the work by Burchfield et al., (2006), by analyzing if this historical development has significant environmental impacts today. While there is a large literature on understanding urban form, VMT, and emissions, very little of it links VMT and emissions to historical development, or explores the timeframe under which these land use policies have an impact.

1.3 The Schaeffer-Sclar Tracked City Framework

Urban form has been shaped by different transportation technologies throughout history. Prior to the automobile, cities were organized around walking and rail transit. The Walking City, typical of the medieval town, was designed to minimize walking distances and so was built very densely (Schaeffer and Sclar, 1980). Households were working units (the bakers, smiths, etc.) where families of employers and employees lived in the same place. Commuting to work, the way we think of it now, was uncommon. Schaeffer and Sclar describe how the Tracked City, of the late nineteenth and early twentieth century, evolved out of the pressures of the industrial revolution and the subsequent need to transport large numbers of workers between the household and the factory. The Tracked City is characterized by a dense commercial center and abundant development along rail lines with little development outside of these areas. This creates a star pattern with development in the center and along the rays of the star as represented in Figure 1.1a (darker
shades indicate higher density).

Figure 1.1: Representation of Urban Form Under Different Transportation Technologies

With the introduction of the Model T Ford that made the automobile affordable, the electric starter that made the car usable by those without the physical strength to turn a crank, and the automatic transmission, the automobile became widespread and changed the shape of the city. In this new city, the Rubber City, people were not constrained to live within walking distance of their place of employment or within walking distance of a rail line that would bring them to work. The areas between the rays of the star could now be developed, as typified in Figure 1.1b. The Rubber City has density along rail lines (or rays of the star), but the automobile allowed this density and settlement to spread out.

Adding to the theory laid out by Schaeffer and Sclar, in the U.S. context, the Rubber City is more often an expanding and restructuring of the Tracked City than an independent form on its own. Many cities have infrastructure and characteristics of the Tracked City that have been built over and adapted to the automobile. Thought of this way, every city is now a Rubber City because it has been built around or retrofitted to the automobile,
but not every city today was a Tracked City. Only those cities that had significant rail prior to the automobile would have had the characteristic urban form of the Tracked City.

Figure 1.2: Passenger Trips on Rail Transit 1900-1965

![Passenger Trips on Rail Transit 1900-1965](image)

*Note: Data from the APTA’s 2013 Public Transportation Fact Book, Appendix A: Historical Tables.*

Figures 1.2 and 1.3 show the trends in transit use and automobile ownership at the beginning of the 20th century and provide evidence for how to empirically define the Tracked City. Rail transit quickly gained ridership in both absolute and per capita terms, adding an average of 442 million trips every year between 1902 and 1920 (American Public Transportation Association, 2013). During this time, vehicle registrations per household were negligible; the car was still a recreational toy for the rich and not a prevalent means of transportation. By 1920, when rail transit passenger trips were at their peak, vehicle
registration rates were still only 1 car per every 3 households. Passenger trips on rail were high throughout the 1920s, but people were clearly investing in the automobile during this time. By the mid-1920s the Tracked City is likely being reshaped. The time period between 1900 and 1920, after the horsecar, but when car ownership rates are very low, is the period of the “Tracked City”.

The Schaeffer-Sclar Tracked City Framework describes the influence that historical transportation technology had on shaping urban form and density. The Tracked City and Rubber City are a summary of complex historical spatial patterns. How long this urban form lasts can have implications for urban planning today. Characteristics common to the Tracked City are a dense center, development along rail lines, and ease of walking and
rail transit. We know that these are traits common to cities with lower CO$_2$ emissions. My hypothesis is that because of path-dependency and the durability of infrastructure, historical urban form persists and continues to influence modern characteristics. The alternative scenario would be if, instead, cities reach a new equilibrium density around the automobile, erasing the density of the streetcar era. The empirical approach is to test if there is persistence in urban form by examining the ability of historical data to predict future urban density and transportation emissions.

1.4 Data Sources

The sample contains 104 U.S. cities in Primary Metropolitan Statistical Areas (PMSAs) that have complete information on relevant variables. Of these 104 PMSAs, 41 had built at least fifty miles of rail by 1907 and 63 had built fifty miles or less (including 8 that did not build any rail). I refer to the first group as “Tracked Cities” and the second as “Rubber Cities”. The PMSAs included in the analysis and the miles of rail built are shown in Figure 1.4.

Data on historical urban rail comes from the 1907 Census Special Report on Electrical Industries section on Street and Electrical Railways. From this source I identify the location and total miles of track within city limits of all urban or interurban rail companies that operated in the year 1907 in the continental U.S. This data is at the company level, so when one company serves multiple cities, the miles are allocated to the main city served (as indicated by the first location listed). This impacts a small number of cities in the sample. In cases where it was ambiguous, the observation was dropped from the sample.

I use city-level population data from the Historical Statistics of the United States,
which includes incorporated places that had a population of at least 100,000 in 1990 and is estimated using constant 1990 boundaries over time (Haines, 2006). I keep only the largest city in each PMSA (since some PMSAs include more than one city) and I use PMSAs as defined by the U.S. Office of Management and Budget in 1999. I get additional variables from the U.S. Census Bureau’s Social Explorer including 2000 population, 1990 land area, and census division. County-level and MSA-level data and shapefiles are from the National Historic Geographic Information System and include median household income and population.

Data on carbon dioxide emissions comes from the Onroad and Nonroad transportation categories of the Vulcan U.S. fossil fuel CO₂ emissions inventory, which is compiled at the county-level for the year 2002 (Gurney et al., 2009). I aggregate the county-level data to
the PMSA¹. The Office of Management and Budget defines PMSAs based on counties that have strong commuting ties. Studying transportation emissions at this level seems most appropriate because it will capture not only the center city, but also the effect that the shape of the city has on its entire transportation region. The Onroad mobile emissions are estimated using engine combustion stoichiometry and vehicle miles traveled by vehicle class and road type. The Nonroad category accounts for mobile sources that do not travel on designated roadways like trains, boats, and snowmobiles. Emissions associated with electrically powered transit are not included in the Onroad and Nonroad emission categories, so I estimate pounds of CO₂ based on energy consumption reported in the National Transit Database and using state-level emissions factors from EPA’s eGRID². I matched agencies to PMSAs based on the zip code of their main office.

1.5 Historical Trends

Density for Tracked Cities and Rubber Cities over time is shown in Figure 1.5. I categorized Tracked Cities as cities that built 50 miles of rail or more and separated Tracked Cities into two groups based on if the city built a moderate amount of rail (50-100 miles) or if the city invested heavily in rail (more than 100 miles). Similarly for Rubber Cities, the graph shows cities that did not invest in any rail (0 miles) separately from cities that built very small transit systems (0-50 miles).

¹The only exception is in New England and in the St. Louis, MO-IL MSA where county boundaries don’t align with MSA boundaries everywhere or when 2002 counties are different from 2000 county boundaries. In these cases I weight the data by proportion of that county’s population in the MSA and then aggregate it.

²See http://www.epa.gov/cleanenergy/documents/state.pdf
What is immediately apparent is that cities that invested heavily in rail transit experienced distinct trends compared to other cities. Shown in blue and purple, Tracked Cities were on average denser in 1890 and continued to be denser in 2000. The Tracked Cities had a period of increasing density until 1930, a stagnation period during the Great Depression, and then again a period of increasing density, at a slower pace, during the 1940s. Even though the proportion of factory employment in central cities declined in every city of more than 100,000 residents between 1920 and 1930 (Schaeffer and Sclar, 1980), and the trend toward suburbanization is well-document during this time (Jackson, 1987), average density does not decrease in Tracked Cities prior to 1950. Transportation policy during this time was not focused on urban areas. In the early 1900s, federal fund-
ing for roads was aimed at the development of rural roads to support getting goods from farm to market and to improve any rural road over which U.S. mail was carried. It was not until the Federal-Aid Highway Act of 1944 that urban roads were first included in a federal funding program.

From 1950 to 1980, density declined in the cities that had originally built the largest rail transit networks (of 100 or more miles). This coincides with the Federal Highway Act of 1956 that authorized funding for the 41,000-mile interstate highway system, with 90% of the cost paid by the Highway Trust Fund and only 10% by states. It also gave states the responsibility for allocating the funds. This is also the decade in which automobile registration rates reached an average of one car per household. Federal housing policy is also often blamed for incentivizing single family homeownership over rental or multi-family development. This had a particularly strong effect as veterans from World War II returned home and started families (Jackson, 1987). Tracked Cities that built a moderate amount of rail transit (50-100 miles), do not appear to have been affected by these commonly cited culprits of suburbanization, and only experience a decline in density from 1970 to 1980.

From 1980 to 2000 density remained relatively constant in Tracked Cities, ending the decline of the previous decades. This comes on the heels of two separate oil crises in 1973 and 1979 and the rise of environmentalism. The Clean Air Act of 1963 was the first federal legislation on air pollution control. That, the Air Quality Act of 1967, and the Clean Air Act Amendments in 1970, 1977, and 1990, set air quality standards, attainment levels, and authorized regulation and enforcement. This meant that federally funded transportation projects were required to demonstrate that they would meet air quality standards. Additionally, the Intermodal Surface Transportation Efficiency Act of 1991, followed by the
Transportation Equity Act for the 21st Century in 1998, created an intermodal approach to highway and transit funding and embedded the goal of creating an environmentally sound transport system.

Rubber Cities did not experience a decline in density at all. It is interesting that even though these cities were exposed to the same federal policies, they continued on the same relative trend for the entire last century.

Overall, this demonstrates different historical trends for cities that came of age at particular times. In addition, to the federal and state transportation policies described above, these trends also reflect changes in the way people perceive cities. For example, the way people want to live has changed over this time period from the Garden City ideal, to the view of the car and highway as progress, through to the more recent environmental movement. The decline in density in the Tracked Cities, especially the ones that historically had the most rail transit, could be indicative of different preferences of the baby boomer generation or of differential effects of local policies common to these cities such as in policing, education. It could be an indication of the difficulty of retrofitting cities whose infrastructure relied on rail transit to automobile technology. Or it could demonstrate that larger agglomerations reacted differently to this set of federal policies. Tracked Cities were denser than Rubber Cities historically and are on average denser than Rubber Cities today, even though they are now connected through the interstate highway system and expansive road network. Whatever the reason for these trends, it is clear that how density evolved over time in Tracked Cities is distinct, even more so if the city was built more around rail transit. In the following sections I empirically evaluate this relationship.
1.6 Relationship with Modern Density and Emissions

Cities that came of age prior to the automobile were built around rail transit. I run a number of regressions to explore how historical rail transit is related to modern density and carbon dioxide emissions using the following equation:

\[ Y = \alpha + \beta \ln(miles_{Rail1907}) + \delta_n controls_n + \varepsilon \]  

(1)

The variables are described, with summary statistics, in Table 1.1. To look at the impact on modern density, the dependent variable, \( Y \), is either \( density_{2000} \), the center city density in 2000, or its natural log, \( \ln(density_{2000}) \). To look at the impact on emissions, the dependent variable, \( Y \), is either \( emissions_{2002} \), the per capita carbon dioxide emission in the transportation sector, or its natural log, \( \ln(emissions_{2002}) \). The coefficient of interest is \( \beta \) on the variable \( \ln(miles_{Rail1907}) \), which is the natural log of miles of interurban rail transit within the city limits in 1907. The control variables are median household income in the PMSA in 1999, \( income_{1999} \), and census division fixed effects, \( divisionFE \), to control for regional variation. Census division fixed effects are a series of dummy variables, each taking on the value of 1 if the city falls within that particular census division and 0 otherwise. There are nine total census divisions. In some specifications I also control for the natural log of center city density in 1890, \( \ln(density_{1890}) \). As shown in Figure 1.5, cities that built rail transit were denser on average in 1890 than cities that did not. I control for historical density to test if the result is being driven by an agglomeration effect instead of historical rail transit. The residual error term is \( \varepsilon \). Robust standard errors are
clustered at the state level.

Table 1.1: Summary Statistics of Dependent and Independent Variables

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Description</th>
<th>Med</th>
<th>Mean</th>
<th>StdDev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>density2000</td>
<td>Center city density measured in persons per square mile using 2000 population and 1990 land area.</td>
<td>3,283</td>
<td>4,043</td>
<td>3,320</td>
<td>832</td>
<td>25,925</td>
</tr>
<tr>
<td>emissions2002</td>
<td>Carbon dioxide emissions in pounds per capita for the transportation sector for the entire PMSA.</td>
<td>3,439</td>
<td>3,473</td>
<td>601</td>
<td>1,558</td>
<td>4,767</td>
</tr>
<tr>
<td><strong>Independent</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>milesRail1907</td>
<td>Miles of rail transit within city limits in 1907. City limits are the city limits defined at that time for the largest city in the PMSA.</td>
<td>33</td>
<td>106</td>
<td>208</td>
<td>0</td>
<td>1,495</td>
</tr>
<tr>
<td>income1999</td>
<td>Median household income in the PMSA in 1999.</td>
<td>42,422</td>
<td>42,976</td>
<td>6,908</td>
<td>28,100</td>
<td>74,335</td>
</tr>
<tr>
<td>density1890</td>
<td>Center city density measured in persons per square mile using 1890 population and 1990 land area.</td>
<td>292</td>
<td>1,147</td>
<td>1,930</td>
<td>5</td>
<td>8,117</td>
</tr>
<tr>
<td>divisionFE</td>
<td>Census division fixed effects. Set of 8 indicator variables for the 9 census divisions to account for regional variation.</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 1.2: Regression Results for Density

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b/se</td>
<td>b/se</td>
<td>b/se</td>
<td>b/se</td>
<td>b/se</td>
</tr>
<tr>
<td>ln(milesRail1907)</td>
<td>893.9**</td>
<td>556.4*</td>
<td>0.0742**</td>
<td>93.38</td>
<td>-0.0499</td>
</tr>
<tr>
<td></td>
<td>(303.8)</td>
<td>(247.4)</td>
<td>(0.0333)</td>
<td>(304.1)</td>
<td>(0.0341)</td>
</tr>
<tr>
<td>income1999</td>
<td>0.110**</td>
<td>0.0000225**</td>
<td>0.0912**</td>
<td>0.0304</td>
<td>0.0000175*</td>
</tr>
<tr>
<td></td>
<td>(0.0350)</td>
<td>(0.00000683)</td>
<td>(0.00404)</td>
<td>(0.00403)</td>
<td>(0.00000682)</td>
</tr>
<tr>
<td>ln(density1890)</td>
<td>919.8</td>
<td>-1330.0</td>
<td>7.190***</td>
<td>-5768.2*</td>
<td>6.001***</td>
</tr>
<tr>
<td></td>
<td>(1054.8)</td>
<td>(1969.1)</td>
<td>(0.437)</td>
<td>(2163.9)</td>
<td>(0.403)</td>
</tr>
<tr>
<td>constant</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>divisionFE</td>
<td>Adjusted $R^2$</td>
<td>0.197</td>
<td>0.374</td>
<td>0.494</td>
<td>0.443</td>
</tr>
</tbody>
</table>

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

The results for density are shown in Table 1.2. In Column 1, without any control variables the relationship between miles of rail in 1907 and density is significant and positive. In Column 2, controlling for median household income and division fixed effects, I find that a 1% increase in miles of rail in 1907 is associated with an increase in center city density of 5.564 persons per square mile. A log-log model is shown in Column 3. The
results are again significant and positive and the interpretation is that a 1% increase in historical rail is associated with a 0.0742% increase in density. In other words, the elasticity of density with respect to historical miles of rail is 0.07. Although these initial results demonstrate a relationship between rail and density, it could be that historical density both influenced the miles of rail built and continues to influence present-day density. In Columns 4 and 5, I control for density in 1890 and the result becomes insignificant, so I cannot dismiss the possibility that historical density is a more important factor in determining future density, although this is analyzed further in the following section.

The results for emissions are shown in Table 1.3. Without any control variables, the relationship between miles of rail in 1907 and carbon dioxide emissions is significant and negative. In Column 2, controlling for income and census division, I find that a 1% increase in miles of rail is associated with a decrease in transportation emissions of 1.107 pounds per capita annually. In the log-log model, shown in Column 3, the results are again significant and negative and the interpretation is that a 1% increase in historical rail is associated with 0.0378% lower emissions. The elasticity between emissions and his-
torical miles of rail is -0.03. When I control for historical density, in Columns 4 and 5, the result is still significant and negative, although somewhat smaller.

These results show that the Tracked City is associated with modern urban characteristics. On average, Tracked Cities are denser cities with lower per capita transportation emissions. To put the results in perspective, a city that built the mean miles of rail in 1907 is predicted to be 2,595 persons per square mile denser and to emit 516 fewer pounds of CO$_2$ per capita today than a city that did not build any rail$^3$. Comparing magnitudes, that would be like doubling the density of the average large city in Texas or Florida in the sample, increasing the density of the average California city in the sample by 50% or increasing the density of New York City by 10%$^4$, which is a rather large effect.

In terms of emissions, a savings of 516 pounds per year compared to the mean transportation emissions of 3,439 is sizable. To compare this to another way of reducing transportation emissions, the estimated average savings of switching from a gasoline to a hybrid vehicle is 5,177 pounds of CO$_2$ per year$^5$. Taking an approximation of 0.70 cars per person in urban areas, if half of them were were replaced with a hybrid vehicle, it would save an estimated 1,800 pounds per capita annually. Considering that the estimated reduction in per capita emissions related to historical urban form may have been accruing year after year, the estimate of 516 pounds per capita calculated for 2002, could be a sub-

$^3$Calculated using the equation $\beta \cdot \ln(miles\text{Rail}_{1907})$ where the mean miles of rail is 106 and $\beta$ is the coefficient from Column 2 in Tables 1.2 and 1.3 for density and emissions respectively.

$^4$These calculations are based on the mean density of 2,582 in Amarillo, Waco, Corpus Christi, Austin, Laredo, Houston, Beaumont/Port Arthur, San Antonio, Abilene, and El Paso; of 2,227 in Orlando, Tallahassee, Tampa/St.Petersburg, and Jacksonville; of 5,732 in San Francisco, Modesto, San Diego, Sacramento, Riverside/San Bernardino, Vallejo/Fairfield/Napa, Santa Rosa, Oakland, Salinas, Stockton/Lodi, San Jose, and Fresno; and of 25,925 in New York City.

stantial environmental benefit over time.

### 1.7 Matching Estimator

Although the initial results demonstrate a relationship between rail, density, and emissions, I cannot dismiss the possibility that the results are being driven, at least in part, by historical density and agglomeration forces that predate rail transit. To address potential endogeneity between historical density and the presence of rail transit, I use a matching estimator. Matching is a quasi-experimental technique that compares treatment and control observations conditional on having similar covariates. The motivation for matching is that if cities are compared that are as similar as possible except that they differ only on having rail transit then the result can come close to capturing the causal effect of being a Tracked City.

I use a binary treatment variable, $\text{Tracked}$, that is equal to 1 if the city had more than 50 miles of rail in 1907 (the “Tracked City”) and equal to 0 otherwise (the “Rubber City”). I use the same dependent variables for modern density and emissions as in Section 1.6. I also consider the relationship with density over time by using density in each decade since 1910 as dependent variables. I match on the same covariates used in the regression analysis which includes the median household income in the PMSA in 1999 ($\text{income}_{1999}$), dummies for each census division ($\text{divisionFE}$), and the natural log of center city density in 1890 ($\ln(\text{density}_{1890})$). I trim the sample so that it includes observations with propensity scores between 0.1 and 0.9, the rule of thumb provided by Crump et al., (2009). This leaves 47 observations of the original 104.
The summary statistics by group for the full and trimmed sample are shown in Table 1.4. This table shows the mean difference across a number of covariates between the Tracked and Rubber Cities in the full sample and in the trimmed sample that is used for the matching analysis. In the second to last column of the table, there are five covariates that are significantly different (using an unequal t-test) between Tracked and Rubber Cities, particularly density and income. The last column of the table shows that, except for the dummy for census division 7, there is no statistical difference between the mean value of each covariate for Tracked Cities as for Rubber Cities in the trimmed sample. In other words, in the trimmed sample, amongst the variables I use for matching, Tracked and Rubber Cities have comparable baseline characteristics.

Nearest-neighbor matching is performed using Stata 14 (StataCorp, 2015). I use Mahalanobis distance nearest-neighbor matching for the statistical advantages over propensity score matching described by King and Nielsen, (2016).

The results by decade are shown in Figure 1.6. These figures plot the average treatment effect every 10 years since 1910 of being a Tracked City. Each point on the graph is the result from the matching estimate for that decade on density in panel (a) and on the natural log of density in panel (b). The bars represent the 95% confidence interval. As an example of how to interpret the graph, panel (a) of the figure shows that the estimated average treatment effect in 1910 is 1,034, meaning that cities would be denser on average by 1,034 persons per square mile in 1910 if all cities were Tracked Cities compared to all cities being Rubber Cities. Again, using 1910 as an example, panel (b) shows that we would expect a 90% increase in 1910 density switching a Rubber City to a Tracked City⁶.

⁶Calculated using the equation \[100 \cdot (e^\beta - 1)\] where \(\beta\) for 1910 is 0.645.
Table 1.4: Mean and Standard Deviation in Full and Matched Samples

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Tracked ( N=41 )</th>
<th>Rubber ( N=63 )</th>
<th>Mean Difference Before Trimming ( N=104 )</th>
<th>Mean Difference After Trimming ( N=47 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>(t-value)</td>
<td>(t-value)</td>
</tr>
<tr>
<td>ln(density1890)</td>
<td>7.17 (1.23)</td>
<td>4.83 (1.33)</td>
<td>-9.15***</td>
<td>-1.81</td>
</tr>
<tr>
<td>income1999</td>
<td>45,531 (6,413)</td>
<td>41,314 (6,754)</td>
<td>-3.21**</td>
<td>-0.76</td>
</tr>
<tr>
<td>division 1 (New England)</td>
<td>0.024 (0.156)</td>
<td>0.032 (0.177)</td>
<td>0.22</td>
<td>-0.21</td>
</tr>
<tr>
<td>division 2 (Middle Atlantic)</td>
<td>0.171 (0.381)</td>
<td>0.032 (0.177)</td>
<td>-2.19*</td>
<td>-0.30</td>
</tr>
<tr>
<td>division 3 (East North Central)</td>
<td>0.244 (0.435)</td>
<td>0.079 (0.272)</td>
<td>-2.16*</td>
<td>-0.88</td>
</tr>
<tr>
<td>division 4 (West North Central)</td>
<td>0.122 (0.331)</td>
<td>0.095 (0.296)</td>
<td>-0.42</td>
<td>0.02</td>
</tr>
<tr>
<td>division 5 (South Atlantic)</td>
<td>0.098 (0.300)</td>
<td>0.159 (0.368)</td>
<td>0.93</td>
<td>0.34</td>
</tr>
<tr>
<td>division 6 (East South Central)</td>
<td>0.098 (0.300)</td>
<td>0.111 (0.317)</td>
<td>0.22</td>
<td>-0.02</td>
</tr>
<tr>
<td>division 7 (West South Central)</td>
<td>0.049 (0.218)</td>
<td>0.206 (0.408)</td>
<td>2.56*</td>
<td>2.13*</td>
</tr>
<tr>
<td>division 8 (Mountain)</td>
<td>0.049 (0.218)</td>
<td>0.095 (0.296)</td>
<td>0.92</td>
<td>n/a</td>
</tr>
<tr>
<td>division 9 (Pacific)</td>
<td>0.146 (0.358)</td>
<td>0.190 (0.396)</td>
<td>0.59</td>
<td>-0.12</td>
</tr>
</tbody>
</table>

* \( p < 0.05 \), ** \( p < 0.01 \), *** \( p < 0.001 \)

Note: Mean difference is based on unequal t-tests.

The overall trends show that there is a lasting effect of rail transit built in 1907 on density in the medium-term, but that this effect is insignificant in the long-term. The magnitude of the effect gets larger from 1910 to 1930, stays relatively constant between 1930 and 1950, and decreases after 1950, mirroring the trends seen in Figure 1.5 and aligning with significant federal changes in transportation and housing policy previously discussed. In percentage terms though, in panel (b), the effect decreases each decade. By 1980, 1990, and 2000, there is no significant effect of the Tracked City on density using the matched
sample. Running the matching analysis for emissions in 2002 is also insignificant (not shown).

Figure 1.6: Average Treatment Effect of Tracked City on Density

For all potential outcome variables (emissions and density in 1910 through 2000), I find a smaller effect in the matching analysis than in the regression results and this likely has to do with the characteristics of the cities included in the trimmed sample. Figure 1.7 is a histogram of the natural log of miles of rail for all cities in the sample in grey, with cities in the trimmed sample highlighted in yellow. What is clear is that to be able to compare cities along these baseline characteristics, I also end up limiting the comparison to cities that had a moderate amount of rail, leaving out the cities that invested the most or least in rail. Identifying treatment as a dummy variable and trimming the sample this way likely explains, in part, the smaller effect size.
1.8 Discussion

Using three different methods I examined the relationship between Tracked Cities, density, and carbon dioxide emissions. The historical trends demonstrate how Tracked Cities, particularly ones that invested heavily in rail at the turn of the century, have experienced distinct trends in density over time compared to other cities. In the regression analysis I find a significant relationship between the miles of rail built in 1907 and density and between historical rail and per capita emissions. These results are rather large, although when I control for historical density as a potential factor, the result of rail transit is insignificant. Finally, in the matching analysis, I find that there is a significant effect on density in the medium-term, but that comparing cities with similar baseline characteris-
tics, there is no significant effect of being a Tracked City on density or emissions in the long-term.

These results taken together show that cities that came of age prior to the automobile may have persistent density at least in the medium-term, and that the relationship between historical rail and historical density deserves additional study to be able to understand if there is a causal mechanism that explains why Tracked Cities continue to have higher density and lower emissions. Specific mechanisms that deserve further study are how rail transit may have locked in specific land uses, industrial composition, distribution of employment, rights of way, travel behavior of individuals, or a stronger zoning and regulatory environment.

Historical density appears to be better at explaining modern density than the miles of rail, but the direction of the effect of rail on historical density or of historical density on rail is unclear. Separating these two effects remains a major methodological challenge in this type of work. First, density in 1890 and miles of rail are highly correlated, which makes them potentially confounding variables in the regression analysis. Second, within my data it is hard to determine which came first. Density in 1890 is unlikely to predate fixed rail transit in every city because many cites built tracked horsecar routes at least as early as the mid-1800s. Some of these tracks were converted to use by the electrical streetcars later on. It is possible that horsecar rail infrastructure may have shaped the density seen in 1890, the control variable that I use. With rail transit data at one snapshot in time, I am unable to study this further. With additional historical data, future work could create a timeline of interurban rail construction, population growth, and urban density by city. Although these are likely to be interrelated, further historical analysis could pro-
vide more context on how development occurred and how rail transit may or may not shape future agglomeration forces. A better understanding of the potential simultaneity between transportation and the built environment is an area for future research.

The matching analysis was one way to try to separate the effect of historical density from rail transit by comparing cities with similar characteristics. This analysis could benefit from including more baseline characteristics, although it may continue to be difficult to assert that urban density has not evolved differently across Tracked and Rubber Cities for unobservable reasons. The idea that Tracked and Rubber Cities may be intrinsically different is particularly salient in light of the fact that cities at the high and low ends of rail investment are not comparable across baseline characteristics. Additionally, there could be other non-linear or threshold effects that are not being captured.

Further, I focused on density because it is relatively easy to measure over time, but future research could test alternative ways of quantifying Tracked Cities including sprawl, compactness, and other measures of urban form. It could also look at outcomes beyond emissions, such as transit use, physical activity, and land use change. Furthermore, future work should test different urban definitions and boundaries in case the results are biased by the urban area used⁷.

Additionally, a question for future research should analyze the ways in which the Tracked City compares to modern Transit Oriented Developments and how comparable the historical experience is to the development of modern TODs. While the advice of Mumford, (1979) to “Forget the dammed motor car and build cities for lovers and friends” is appealing, the car is here to stay and offers benefits such as shorter, direct commutes,

⁷This phenomenon is referred to as the modifiable areal unit problem.
and larger houses (Glaeser and Kahn, 2004). This could mean that the development that occurred in 1907 is not possible to replicate today. Given the relationships demonstrated here, it would be interesting to see how modern TODs are comparable to cities that came of age prior to the automobile. Because Tracked Cities have significantly higher density today and lower emissions than cities that did not invest as heavily in rail, it could, by extension indicate the likely future trajectories for modern TODs and the likelihood that they will have the long-term intended benefits.

Finally, this research indicates that there may be a relationship between the historical spatial development of a center city and its entire future metropolitan region. Data on historical miles of rail were at the city level, but there is a relationship between the Tracked City and CO$_2$ emissions in the entire region. The metropolitan region used, the PMSA, is constructed based on the number of commuters to the center city. The fact that the finding for emissions is significant at the regional-level, could mean that the emissions in the city center are so low as to dominate the effect at the regional scale or, even more interesting, that the city center may effect the shape, travel patterns, and emissions of an entire region. This idea could merit future research.

1.9 Conclusion

The results demonstrate that Tracked Cities followed a distinct historical trajectory and that they continue to be denser and have lower per capita transportation emissions in the future. I use the Schaeffer-Sclar Tracked City Framework to describe the particular urban form of cities that developed densely around rail transit prior to the automobile. One
benefit of this framework is that it captures a number of spatial characteristics that are correlated, which considered jointly may have a larger combined effect on emissions. The miles of rail built in 1907 is used to describe cities that came of age prior to the automobile and this variable explains some of the variation in present-day density and emissions across cities. For cities that invested heavily in rail the effect is relatively large. Because Tracked Cities not only have more rail, but are also denser, I run a matching analysis to compare cities that have similar initial characteristics except that they differed based on rail investment. In the matching analysis I continue to find a relationship with density that lasts in the medium-term (more than 60 years later) in Tracked Cities. These findings align with historical trends in federal and local policies in these decades. On the whole, the results show that there is persistence in urban density, that this explains some of the variation in per capita carbon dioxide emissions, highlighting that the way a city develops may have long-term environmental consequences.

The U.S. cities that invested more heavily in rail transit have much higher density and lower emissions a century later. A number of cities in the U.S., including Los Angeles, Milwaukee, Detroit, and others, are expanding their existing systems or are building new rail and streetcar systems, but they may not see very large changes to long-term density or emissions because none of these systems are planned to be very extensive. In other parts of the world, particularly cities in Latin America, Africa, and East Asia, where car ownership rates are still relatively low, and in China, where rail transit development has been more extensive, there may be more significant impacts on urban density and lasting environmental benefits of developing as a Tracked City. The built environment is durable, and urban infrastructure is costly to alter post-construction, so decisions made early in
a city’s history could have lasting effects. Encouraging dense development around rail transit may be an effective strategy, given its potentially longer-lasting impact, and the time periods over which these benefits accrue should be weighed against the costs and benefits of other strategies for reducing emissions or increasing urban form.
2.1 Introduction

Over the last decade, bikesharing systems have rapidly expanded throughout the United States (Fishman, Washington, and Haworth, 2013; Shaheen et al., 2014). However, it remains unclear how this mode of shared transportation interacts with pre-existing public transit systems. In particular, the overall impact on transit ridership has yet to be quantified. For this study we focus specifically on the impact that opening a bikesharing system had on daily bus ridership in New York City.

There are a number of possible ways that bikesharing could impact bus ridership. As a direct effect, a bikesharing system may be a substitute or a complement to the pre-existing bus network. For example, a person could use bikesharing in lieu of a trip they would have taken by bus. This kind of substitution would result in a loss of bus ridership at a rate of one-to-one. Alternatively, a person could use bikesharing in addition to public transit, which is commonly referred to as solving the first- and last- mile problem (Shaheen, Guzman, and Zhang, 2010). This complementary situation could lead to an in-
crease in bus ridership. As a third option, bikesharing may generate new trips, such as for recreational use, which would not impact bus ridership. For different users or at different times, bikesharing and buses could be interrelated in any of these three ways.

An important, but often overlooked, aspect is the indirect effect that a bikesharing system may have on the travel behavior of non-members. There are numerous possible indirect effects. For example, if bikeshare users substitute away from buses, a reduction in bus passengers and crowding could encourage a new group of travelers to begin riding the bus, which could minimize the overall impact on bus ridership. In another scenario, opening a bikesharing system could encourage people to ride private bicycles more, particularly if they now perceive the city to be more bike-friendly. If these trips would otherwise have been made by bus, then there could be a reduction in bus ridership at a rate greater than one-to-one. The ways that bikesharing could impact how non-members travel remains largely unexplored, and it is currently unknown what this net effect of bikesharing is on bus ridership.

In this study, we measure the impact that opening a bikesharing system had on the bus network in New York City using daily route-level bus ridership data. Because the bikesharing system, Citi Bike, had a phased implementation, we treat it like a natural experiment. We divide bus routes into control and treatment groups based on if they were in the areas that received bikesharing stations or not. A difference-in-differences regression model allows us to isolate the effects of the introduction of bikesharing from other area, group, and time effects and establish a causal link between bikesharing and bus ridership. Estimates from our preferred model indicate that every thousand bikesharing docks along a bus route is associated with a 2.42% reduction in daily unlinked bus trips.
on routes in Manhattan and Brooklyn. In a second model that also controls for bike lane infrastructure, we find a 1.69% reduction in bus trips. These results are statistically significant and hold under a variety of specifications. The rest of the paper is organized as follows. Section 2.2 provides an overview of previous research and gaps in the existing literature. Section 2.3 provides background to understand the natural experiment and identification strategy. Section 2.4 describes the data we use, and Section 2.5 describes how we construct the control and treatment groups and the regression methodology. In Section 2.6, we present the results. Section 2.7 describes limitations and future research areas. We discuss the implications of the findings and conclude in Section 2.8.

2.2 Prior Research on Bikesharing and Public Transit

In a literature review on bikesharing, Fishman, Washington, and Haworth, (2013) identify two themes that pertain to the relationship between bikeshare and public transit: modal integration and modal substitution. Modal integration focuses on the location of bikeshare infrastructure near transit stations so that passengers can use bikeshare in conjunction with transit. Modal substitution refers to trips made by bikeshare that were previously made by transit. In another recent literature review, Ricci, (2015) notes that more attention has been paid to understanding how much bikesharing shifts people away from the automobile and that the results regarding public transport are mixed. We have found that there are a limited number of studies that pertain to these two transit-related themes; the most relevant ones are discussed in detail in the following paragraphs.

In terms of modal integration, bikeshare operators typically locate stations close to
transit stops to facilitate transfers between the two modes. Numerous studies have found that variables relating to public transit can be a significant predictor of bikeshare usage (Fishman et al., 2014; Hampshire and Marla, 2012; Nair, Miller-Hooks, and Hampshire, 2013; Rixey, 2013; Sato, Miwa, and Morikawa, 2015). In New York City, bikesharing stations that are located near subway stations, particularly stations with a high number of average monthly subway boardings, saw higher bikeshare usage (Noland, Smart, and Guo, 2016). These findings suggest that there could be a complementary relationship between bikesharing and transit, although for New York City, this relationship has only been explored for the subway and remains unknown for the bus system.

Regarding modal substitution, bikeshare member surveys typically find that many people reduce their bus use as a result of bikesharing, although the size of the effect varies across cities and even within a city (Buck et al., 2013; Fuller et al., 2013; Murphy and Usher, 2015; Shaheen, Martin, and Cohen, 2013; Shaheen et al., 2011; Tang, Pan, and Shen, 2011). In a survey of Montreal, Washington D.C., Toronto, and the Twin Cities, 17% to 47% of respondents reported that they decreased their bus usage as a result of bikesharing, although within these same cities 2% to 14% reported increasing their bus usage. Even though they found an overall substitutionary effect, there were members using bikeshare as a complement to buses as well (Shaheen, Martin, and Cohen, 2013). In subsequent research, Martin and Shaheen, (2014) found that bikeshare members in Washington D.C. living in the urban core were more likely to report decreases in bus use as a result of bikesharing, while respondents living in the urban periphery were more likely to report increases. However, this relationship did not hold in Minneapolis, where respondents reported increasing and decreasing usage in almost equal proportion whether they lived
in the urban core or periphery. The authors posit that bikesharing is more likely to act as a complement in cities with lower population density and less dense transit networks. Similarly, another survey in Montreal found that the majority of bikeshare users shifted away from public transit. They also asked non-users about their travel behavior and found that 3% of respondents who do not use bikeshare reported shifting to public transit as a result of bikesharing (Fuller et al., 2013). They confirmed their hypothesis that, as a large-scale change in the built environment, bikesharing could have impacts on active travel beyond the direct effect on bikeshare members. While there are no publicly available surveys of bikeshare members in New York City, survey results from other cities begin to quantify the proportion of bikeshare users who may have a direct impact on transit ridership by changing their travel behavior; however, these studies do not quantify the magnitude of that impact in terms of total transit trips gained or lost. In addition, the surveys of only bikeshare members are unable to capture indirect effects on transit from changes to the travel behavior of non-members, although there is some evidence that demonstrates that bikesharing systems can have broader indirect effects.

There are two noteworthy prior studies that examine the magnitude of the impact of bikeshare on transit ridership. The first examined the impact of bikesharing on rail ridership in Washington D.C., which had the second largest bikesharing system in the United States at the time. Using regression analysis, the authors found that a 10% increase in bikeshare trips is associated with a 2.8% increase in Metrorail ridership (Ma, Liu, and Erdoğan, 2015). Although they find a significant relationship, the cross-sectional study design makes it difficult to disentangle the effect of bikesharing from other trends in rail ridership, and it is possible that other trends in rail ridership could have driven the effect.
The second noteworthy study, which is perhaps the most relevant reference for this research, is a study on the impacts of real-time transit information on bus ridership in New York City (Brakewood, Macfarlane, and Watkins, 2015). The study analyzed route-level weekday average bus ridership per month over a three year period from 2011 to 2013 using panel regression. The availability of bikesharing was modeled as a binary control variable for all bus routes in Manhattan and Brooklyn after the bikesharing program commenced, and the authors found that it had a significant, negative effect on route-level bus ridership (over 500 daily bus trips per route in Manhattan and approximately 375 daily bus trips per route in Brooklyn). However, the authors note that the magnitude of the coefficient appeared to be unrealistically large. Performing a back of the envelope calculation, the reduction in bus trips on routes in Manhattan and Brooklyn would be equivalent to very large percentage (almost all) of bikesharing system’s average weekday ridership in 2013. Therefore, the authors recommended further study to better understand the complex relationship between bus ridership and bikesharing.

By quantifying the impact that bikesharing has on bus ridership, we contribute to the literature in the following ways. First, our research design is better suited for quantifying a causal relationship than geospatial and cross-sectional studies. Second, we study the impact to buses, which has been largely overlooked in prior studies that have focused on rail systems. Third, we capture aggregate level impacts to the transit network. Although surveys provide a good assessment of the causal way bikeshare users alter their travel behavior, they typically do not capture indirect effects of the behavioral change of non-members, and they require a number of assumptions to estimate the net impacts to transit ridership. Furthermore, we account for the varying intensity of bikesharing infrastruc-
ture, an improvement over studies using a dummy variable to capture the effect. Finally, this relationship has not been well studied in New York City, which has the largest public transit system and largest bikesharing system in the United States at the time of this writing.

2.3 Background

In the following paragraphs, we provide background information about the bus and bikesharing systems. Then we compare the two systems based on their prices, ridership trends, and trip characteristics. Last, we describe specific transportation changes that were happening in New York City at this time.

Bus Service in New York City

New York City is composed of five boroughs: Manhattan, Brooklyn, the Bronx, Queens, and Staten Island. Most local bus service is operated by New York City Transit (NYCT) under the umbrella organization of the Metropolitan Transportation Authority (MTA). NYCT operates the largest bus system in the country, which, in 2013, accounted for almost 15% of unlinked passenger bus trips nationwide and over 85% of trips in New York City (American Public Transportation Association, 2015). The NYCT bus system includes approximately 200 fixed routes. This study focuses on 85 bus routes located in the boroughs of Manhattan (34 routes) and Brooklyn (51 routes).

¹The remaining were trips on routes operated by the MTA Bus Company. Because the MTA Bus Company operates primarily in Queens, we do not include these routes in our study.
Bikeshare in New York City

New York City’s bikesharing network is the densest in the U.S. with 19.7 bikesharing stations per square mile compared to 6.8 in Chicago and 4.4 in DC (Gordon-Koven and Levenson, 2014). Phase 1 of the bikesharing system opened on May 27, 2013 with a dense network of stations in southern Manhattan and downtown Brooklyn, while the rest of the city received no bikesharing infrastructure. As explained in Section 2.5, we use the uneven geographic coverage to split the city into control and treatment areas, and within the treatment area, we quantify the amount of bikesharing infrastructure available. Each bikesharing station has a number of bike docks where a user can lock or unlock an individual bike. Figure 2.1 shows the location of stations and the amount of docks at each station, highlighting how the density of docks and stations varies. The number of docks per station varies from 3 to 62 with Manhattan having a slightly higher mean number of docks per station than Brooklyn. The total number of bikesharing stations in Manhattan is also higher at 262 compared to 82 in Brooklyn.

The vast majority of bikeshare trips (over 90%) are taken by annual members (Kaufman et al., 2015), who provide basic demographic information, including age and gender, at the time of registration. During our study period, the median age for bikeshare trips taken by annual members was 35 years old and 77.7% of those trips were taken by men. In contrast, the median age for bus passengers in the New York City region is higher and a larger proportion are female (New York Metropolitan Transportation Council and North Jersey Transportation Planning Authority, 2014; Seltzer, 2014).
Bus and Bikeshare Prices

To ride the bus, passengers pay with cash or use a MetroCard, which works on NYCT and MTA Bus Company buses and the subway. There are a variety of payment options and fees, including single-ride tickets, unlimited period passes, discounts for larger purchases, fees to obtain a new MetroCard, reduced fare passes for disabled or elderly passengers, free fares for students, and a number of other payment options. On March 3, 2013 (approximately three months prior to the opening of the bikeshare system), the base bus fare rose from $2.25 to $2.50, the price of a 7-day unlimited MetroCard rose from $29 to $30,
and the cost of a 30-day unlimited MetroCard rose from $104 to $112 (Metropolitan Transportation Authority, 2012). To use a bikeshare bicycle, riders have three options to pay: a 24-hour pass costing $9.95, a 7-day pass costing $25, or an annual membership costing $95. This means that the one-week cost is similar across the two systems at $25 and $30, but that the annual cost for unlimited trips is much higher on the bus ($95 for an annual bikeshare membership and up to $1,344 for twelve unlimited monthly bus passes).

Bus and Bikeshare Ridership, Speed, and Trip Distances

Both the bus and bikeshare systems in New York City exhibit strong daily and seasonal ridership trends. Both systems have higher ridership on weekdays than weekends with peaks during the morning and afternoon commutes (New York City Department of Transportation, 2016; Schneider, 2016). Bikeshare trips are high from mid-May to mid-October, while bus ridership is high in the fall and spring. During our study period from May 27, 2012 to July 26, 2014 (excluding a two-month adjustment period after bikesharing opened), daily bikeshare trips ranged from a minimum of 978 to a maximum of 45,667 with an average of 26,072 daily bikeshare trips. There were 951,176 average daily unlinked bus trips in Manhattan and Brooklyn during this time, which is an order of magnitude larger than daily bikeshare ridership. Daily bus route-level ridership ranged from a minimum of 279 to a maximum of 48,785, with a mean of 11,231 daily trips per route. Average daily bus ridership has been declining, such that citywide bus ridership fell 2% between 2014 and 2015, with ridership in Manhattan falling by 6% in 2014, according to the New York City Department of Transportation, (2016). We can see this slight decline in Figure 2.2, which
show the average daily ridership per month during the study period for all bus routes in Manhattan and Brooklyn and for the bikeshare system.

**Figure 2.2: Average Daily Ridership by Month in Manhattan and Brooklyn**

During our study period, average bikeshare speed was 8.4 mph and average trip distance was 1.7 miles (CitiBike, 2015). According to estimates from the New York City DOT, average bus speed is frequently over 10 mph, particularly on arterial roads between neighborhoods, but is often 4 mph or less in central business districts like Midtown Manhattan (New York City Department of Transportation, 2016). One example given by New York University’s Rudin Center estimates that “a mile-long bus trip across 34th Street could take more than 20 minutes but a Citi Bike cuts the same trip down to 10 minutes or less, depending on the rider” (Kaufman et al., 2015).
The bikesharing and bus systems in New York City are comparable across a number of characteristics, although there are some instances where bikesharing may be more efficient. Because of the similarity in travel speeds, we hypothesize that bikesharing may act as a substitute for bus trips in New York City. Additionally, because daily bus ridership is magnitudes larger than daily bikeshare ridership, we do not expect to find a sizable impact on overall bus ridership. Instead, quantifying the size of the effect can tell us more about the degree to which these systems interact with one another in New York City.

Changes to the Transportation Network

Finally, there were other transportation changes happening during this time that are worth noting. First, bicycling was growing in New York City. In 2014, 25% of New Yorkers reported that they rode a bike at least once in the past year. Annual cycling trips went from 98.6 million in 2011 to 153.3 million in 2014 (New York City Department of Transportation, 2017). During the same time period, New York City increased investment in bicycle infrastructure including bike lanes, bike signage, and signals, and in 2013 opened a bikeshare system.

Additionally, Select Bus Service (SBS) was introduced on a small number of bus routes during the study period. SBS is a form of rapid bus service where passengers pay before boarding the bus, and buses have designated travel lanes and traffic signal priority in some areas. Another change was the introduction of Bus Time, which provides passengers with real-time bus information via web-based and mobile interfaces and rolled out to some routes during the study period. A third change that happened to the broader transport
system during this time was the introduction of the Boro Taxi program, which allowed for-hire vehicles (besides yellow taxis) to pick up street hail passengers anywhere in the five boroughs except in the Manhattan Core (south of East 96th and West 110th St) (New York City Taxi and Limousine Commission, 2013). Furthermore, ridehailing services, such as Uber and Lyft, began operating in New York City in 2011 and grew in popularity during this time. These noteworthy transportation network changes are explained further in Section 2.5.

2.4 Data Sources

Bus data were made available through a request to NYCT. The data include daily unlinked bus trips per route, daily unlinked bus trips by route split by fare type used (full, reduced, or student fare), and scheduled revenue miles per route. From the scheduled revenue miles data and from MTA press releases, we have information about when certain routes began operating Select Bus Service, when they began offering Bus Time real-time information, and when the Access-A-Ride MetroCard program was introduced. We use any route that primarily serves Manhattan or Brooklyn based on the bus route name, but we exclude express routes and routes that pass into Manhattan or Brooklyn but primarily serve other boroughs. We combine a small number of bus routes that operate on sections of the same right-of-way and are scheduled together². Additionally, we exclude dates when subway or bus service was canceled due to severe weather³. We use publicly available data with the

²We combined the M102 and M103 with the M101 and the M16 with the M34 and the B69 with the B67 routes.

³We exclude 8/27/2011-8/29/2011 (Hurricane Irene) and 10/28/2012-11/8/2012 (Superstorm Sandy).
latitude and longitude of each bus stop along all NYCT bus routes as of June 2015 that can be downloaded from the MTA’s developer data webpage⁴ (Metropolitan Transportation Authority, 2015). The models presented in the following section were also tested using the latitude and longitude of each bus stop as of 2010, with no significant change in the results. We imported this data into ArcGIS using the Display GTFS Route Shapes tool⁵ and used ArcGIS® software by Esri version 10.3.1 and the Light Gray Canvas basemap to generate the maps presented here ⁶.

Citi Bike data are publicly available⁷(CitiBike, 2015). We downloaded daily total ridership and membership data for the period May 27, 2013 (the launch date) to December 31, 2014. Additionally, we downloaded trip history data for the same period that includes the date and station location (latitude and longitude) where each bike trip begins. Finally, we downloaded the Citi Bike Station feed data that includes the number of docks at each bike station⁸.

A map of the Boro Taxi service area and launch date is publicly available from the New York City Taxi and Limousine Commission (New York City Taxi and Limousine Commission, 2013). Miles of bike lanes and date built came from the New York City Cycling Map shapefile published annually by NYC DOT⁹.

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⁴Available at http://web.mta.info/developers/developer-data-terms.html
⁵The Display GTFS Routes Shapes was created by Melinda Morang at Esri and was downloaded from http://transit.melindamorang.com.
⁶Basemaps in all the images are the Light Gray Canvas Map by Esri, DeLorme, HERE, and MapmyIndia.
⁷Citi Bike system data were made available by the operator of New York’s bikesharing service, NYC Bike Share, LLC and can be found at https://www.citibikenyc.com/system-data
⁸To calculate the number of docks per station we used the average number of docks listed from daily live feed data beginning in July averaged over the whole time period. In rare cases where data on the number of docks was missing, we assumed that these stations had the mean number of docks for the sample.
⁹Available at http://www.nyc.gov/html/dot/html/about/datafeeds.shtml#bikes
2.5 Methodology

This section describes the methodology, beginning with how we divide the bus routes into a control and treatment group based on variation in geographic coverage of the bikesharing network in Section 2.5. Next, we describe the difference-in-differences identification technique in Section 2.5 and how it can be estimated using Ordinary Least Squares regression in Section 2.5. We present visual evidence that bus ridership is falling on routes in the treatment compared to the control when treatment is defined by geographic coverage of bikeshare. In Sections 2.5, 2.5, 2.5, and 2.5, we explain variations to the main specification that address the robustness of the model including controlling for cycling infrastructure, controlling for a time trend in the treated group, changing the way we quantify treatment intensity, and performing a placebo analysis. Finally, in Section 2.5, we present a model using an alternative control and treatment group based on the type of bus fare payment used. This alternate model addresses some concerns about the endogeneity of the intervention itself and additional potential omitted variables.

Definition of Treatment Based on Intensity of Geographic Coverage of Bikesharing

One contribution of this research is quantifying the interrelationship between the bikesharing and bus systems based on the intensity of bikesharing infrastructure. As described in Section 2.3 and shown in Figure 2.1, the number of stations and the number of docks at each station varies considerably. We develop a treatment measure based on the number of docks located near each bus route to capture the potential availability of a bikeshare
Using data on bus route and bikesharing station locations, we count the number of bikesharing docks that fall within a 0.25 mile catchment area of the bus route. A quarter mile is commonly used by transit planners as the distance people will walk to reach a bus stop (Walker, 2012). Figure 2.3 provides an illustration of how this measure is calculated along one example route, the M23 bus. In the figure, the bus route is shown in black, the catchment area is in orange, the bikesharing stations are light blue, and the bikesharing stations that fall within the catchment area are indicated by an orange outline. The circled number indicates how many docks are at each bikesharing station. We sum the number of docks over the entire route. In this example, there are a total of 1,172 docks along the M23 bus route. This treatment variable captures the fact that larger stations can have more bikes available, which better reflects the variation in intensity of bikeshare infrastructure. Figure 2.4 shows this treatment measure for all the bus routes in the sample. We test a few alternate treatment variables as described in Section 2.5.
Figure 2.4: Treatment Variable Based on the Number of Bikesharing Docks Along the Bus Route

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>Control</th>
<th>Treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std.Dev.</td>
<td>Min.</td>
</tr>
<tr>
<td>Manhattan and Brooklyn</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Docks Per Route</td>
<td>11,858</td>
<td>1,359</td>
<td>1,045</td>
</tr>
<tr>
<td>Manhattan</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Docks Per Route</td>
<td>9,596</td>
<td>2,002</td>
<td>1,029</td>
</tr>
</tbody>
</table>
Difference-in-Differences Research Design

The natural experiment afforded by the phased roll out of bikesharing allows us to use a difference-in-differences identification strategy. A difference-in-differences model uses panel data to compare the outcome in one group that receives treatment to a control group during the study period in an attempt to quantify the causal impact of a policy. The difference between the two groups before the policy went into effect is subtracted from the difference between the two groups after the policy went into effect. The difference of these two differences (hence the name) is the estimated effect of the policy. Take for example, ridership ($BusRiders_{jat}$) on bus route $j$ in area $a$ at time $t$. Let bus routes in northern Manhattan be the control group ($a = N$), bus routes in southern Manhattan be the treatment group ($a = S$), one time period before the bikesharing system opened ($t = 0$), and one time period after it opened ($t = 1$). The average treatment effect is given by:

$$(E[BusRiders_{jat} | a = S, t = 1] - E[BusRiders_{jat} | a = S, t = 0]) - (E[BusRiders_{jat} | a = N, t = 1] - E[BusRiders_{jat} | a = N, t = 0]) = \beta \quad (2.1)$$

Here, $\beta$ is the causal effect of interest and, as described in the next section, it can be estimated using Ordinary Least Squares regression.

The major advantage of this identification strategy is that it removes biases caused by the permanent differences between the control and treatment groups, as well as biases caused by time trends impacting the entire sample. For example, if bus routes in the treated area consistently have higher ridership than routes in the control area, this will be washed out in the first difference ($E[BusRiders_{jat} | a = S, t = 1] - E[BusRiders_{jat} | a = S, t = 0]$).
so that route size will not have a net effect on $\beta$. Any characteristics of the control or treatment group that do not change over time are accounted for in this way. This is important because there are differences between population groups in terms of race, income, and education in areas that received bikesharing compared to nearby areas in New York City (Ursaki and Aultman-Hall, 2016). Similarly, this methodology controls for changes that happen over time and have the same impact to both groups. For example, if citywide population growth causes ridership to increase by a constant in the second period in both the control and treatment groups, taking the difference of the differences would result in a net effect of zero from the population increase. This example demonstrates the second feature of difference-in-differences, which is that time-varying factors that affect both groups can be accounted for by the second difference.

Potential omitted variables that are still a concern are changes that occur when the bikesharing system opened and impact the treatment group differently than the control group. Whenever possible, we account for these types of potential omitted variables by adding control variables to the model. Another concern is endogeneity of the intervention itself; in other words, if the treatment area was chosen precisely because it would have a different impact on bus transit. To address these concerns, we also use an alternative way of splitting the sample into control and treatment groups as a robustness check in Section 2.5.
Regression Methodology Using Geographic Coverage of Bikesharing

We can use ordinary least squares regression to estimate the effect of bikesharing on bus ridership based on the geographic coverage of bikesharing. We generalize the basic two-period and two-group difference-in-differences model discussed in the previous section to include multiple time periods and groups and to account for the intensity of bikesharing treatment. Our preferred model takes the following form:

\[
\text{LnBusRiders}_{jt} = \alpha + \beta \text{BikeOpen}_t \times \text{BikeArea}_j \times \text{Docks}_j + \\
\delta \text{DateFE}_t + \gamma \text{RouteFE}_j + \lambda \text{Controls}_{jt} + \varepsilon_{jt} \quad (2.2)
\]

Here, \( \text{LnBusRiders}_{jt} \) is the natural log of ridership on day \( t \) on bus route \( j \), and we use total daily unlinked bus trips per route on buses operated by NYCT from May 27, 2012 to July 26, 2014, excluding a two-month bikeshare adjustment period from May 27, 2013 to July 26, 2013. We estimate the model for Manhattan and Brooklyn combined and for Manhattan alone. We take the natural log of bus ridership because the pre-treatment average levels of daily bus ridership in the treatment group are much higher than in the control group. Since the difference-in-differences effect is sensitive to functional form, we use the natural log of the differences to prevent changes in ridership on routes with larger total ridership from obscuring the effect. \( \text{BikeOpen}_t \) is an indicator if the date is on or after May 27, 2013, which is when the bikesharing system opened. There are 354 days in the control period and 365 days in the treatment period (11 days in the control
period were excluded due to severe service changes from Superstorm Sandy). $BikeArea_j$ is an indicator if any part of the bus route is near a bikesharing station.

Our variable of interest is $BikeOpen_t \times BikeArea_j \times Docks_j$, which is the interaction of $BikeOpen_t$ and $BikeArea_j$ weighted by $Docks_j$, a variable measuring the number of bike docks (in thousands) near the bus route. This variable identifies routes in the treatment area after the bikesharing system opened weighted by the intensity of bike-share docking infrastructure. Construction of this variable was explained in Section 2.5 and alternate measures of treatment intensity are described in Section 2.5.

We include date fixed effects ($DateFE_t$), which control for daily system-wide variation, and route fixed effects ($RouteFE_j$), which control for characteristics of each route that do not vary over time. $Controls'_{jt}$ is a vector of area- and time- varying characteristics, described in the next paragraph. The residual error term is $\varepsilon_{jt}$. Because of the potential for serial correlation across dates in this long time series, we use bootstrap standard errors (Bertrand, Duflo, and Mullainathan, 2004). We also cluster the standard errors at the bus route level (Cameron and Miller, 2015). Estimations were completed in Stata versions 12 and 14 and the carryforward, estout, erepost, and nearstat packages were also used (Jann, 2005, 2007; Jeanty, 2010; Kantor, 2004; StataCorp, 2015).

The vector $Controls'_{jt}$ includes variables for scheduled revenue miles of bus service, the introduction of Select Bus Service, the roll out of real-time bus information, and the introduction of the Boro Taxi program. We include the natural log of total schedule revenue miles, which captures the total miles that buses on a particular route are scheduled to travel that day while in revenue service, because the level of bus service is an important predictor of bus ridership (Evans IV et al., 2004). It takes into account differences in route
length and frequency of service between routes and provides an indication of the level of service available each season¹⁰. For Select Bus Service, we include a dummy variable to indicate if any bus along a route was operating as SBS that day. Regarding real-time bus information, we include a dummy variable to indicate if that bus route had Bus Time on that day. Changes to the taxi service were modeled using a dummy variable for any route that has stops within the Boro Taxi service area for dates on or after August 8, 2013, which is when the first Boro Taxi ride occurred.

An identifying assumption for our analysis is that, in the absence of treatment, the trend in the treatment group would follow the same trend as the control group. In Figure 2.5 we provide graphical evidence showing that prior to the bikesharing system opening, ridership in the control and treatment groups were following parallel trends. This figure shows the trend in average daily route-level bus ridership for each month with the study period of May 27, 2012 to May 26, 2013 (pre) and July 27, 2013 to July 26, 2014 (post) indicated by the gray boxes. The treatment group shown here includes bus routes in Manhattan or Brooklyn that have at least one bikesharing dock within 0.25 miles of the route, and the control group includes bus routes that are not near any bikesharing docks. We see in the graph and accompanying table that treatment routes have higher average ridership than control routes, that the groups are following a similar trend prior to bikeshare opening, and that there is a decrease in average bus trips in the treatment group compared to the control group after the bikesharing system opens (indicated by the vertical dashed line in the graph).

¹⁰NYCT sets scheduled revenue miles per route for each pick, which is similar to season and runs roughly from January-March, April-June, July-August, and September-December.
Cycling Infrastructure

In a similar timeframe as the opening of the bikesharing system, New York City was investing in cycling infrastructure, such as bike lanes and signals. Cycling infrastructure
has been shown to have a positive relationship with levels of private cycling (Pucher and Buehler, 2011), which could, in turn, also impact bus ridership. In the 12-months prior to opening the bikesharing system, 31 miles of bike lanes were installed with 18 miles located in the same area as the bikesharing system. In the 14-months after the bikesharing system opened, 55 more miles of bike lanes were installed including 7 miles in the bikesharing area. In our main specification, we do not separate this potential effect; however, in a second specification, we test how much of the result is being driven by cycling infrastructure and how much is being driven by bikesharing infrastructure by controlling for bike lanes. Specifically we include a control variable for the miles of bike lanes that are within 0.25 miles of each bus route over the course of the study period using the date that the bike lane was installed. In terms of the difference-in-differences identification strategy, bike lanes is a potential omitted variable because the amount of cycling infrastructure varied across the control and treatment areas during our study period. However, in our regression framework it is a confounding variable. Because it is highly correlated with our variable of interest, including it as a control makes it difficult to untangle the impact that bike lanes had on bus ridership from the impact of the bikesharing system. Therefore, we present this analysis to confirm that it is not driving our main result.

**Time Trend**

We want to rule out the possibility that our results are being driven by some general downward trend in bus ridership on treated routes. To do so, we include a linear time trend interacted with the indicator for treated routes, $BikeArea_j$, in some of our model
specifications. Both a linear and quadratic trend were fit, but because the results are similar only the linear time trend is presented. While this variable could account for any number of trends specific to the treatment groups, we were particularly concerned that ridehailing services, such as Uber, may be impacting bus ridership more in the treatment groups. Because we do not have the data to explicitly model riderhailing for the duration of our study period, we use this specification as another check of the main result.

**Other Measures of Treatment Intensity**

In addition to our preferred treatment measure based the intensity of bikeshare docking infrastructure near bus routes, we develop three alternative treatment measures. The first alternative treatment measure is a dummy variable that is equal to one if the bus route is within a 0.25 mile radius of at least one bikesharing dock, and zero otherwise. The second alternative treatment measure is the total number of bikesharing stations within 0.25 miles of the bus route. This is similar to the treatment measure based on docks. Our third alternative treatment measure is the number of bikesharing trips originating within 0.25 miles of the bus route each day. This last measure varies daily, while the rest of the measures are constant over time. Figures 2.6a, 2.6b, and 2.6c show each of these treatment measures for routes in the sample.

The treatment measure based on the number of bikesharing docks remains our preferred measure for a number of reasons. First, we do not expect the impact to be the same for a bus route that is near only one bikesharing dock as a bus route that has bikesharing docks along its entirety. While a dummy variable identifies routes that may be impacted,
it is a rather coarse measure considering the variation in bikesharing infrastructure across the city. Second, the treatment measures based on stations and on docks are highly correlated, but the measure based on docks has the advantage that it captures the variation in the size of stations and the fact that larger stations can have more bikes available. We feel this is a better reflection of being able to check out a bikesharing bicycle. Finally, although the treatment measure based on bikesharing trips accounts for the variation in daily travel, we prefer to use infrastructure-based measures. Using bikesharing trips
as the causal variable of interest may violate the conditional independence assumption, upon which causal inference relies. For example, if an overcrowded bus prompts someone to use bikesharing, then the outcome variable (bus ridership) is actually influencing the causal variable of interest (bikesharing) instead of the other way around. If this happens we can no longer interpret the results as quantifying a causal effect of bikesharing. With the infrastructure-based measures, there’s no reason to believe that variation in daily bus ridership would change the level of bikesharing infrastructure available. Additionally, even though infrastructure-based measures do not reflect actual day-to-day bike availability, the number of docks is associated with actual usage (Noland, Smart, and Guo, 2016). We prefer the infrastructure-based measure of bikesharing docks to alleviate the potential “reverse causality” situation described, although we include results using bikesharing trips.

**Placebo Model**

We also estimate a placebo difference-in-differences model. We run the same analysis as our main specification but use the time period from May 27, 2011 to May 27, 2013. We use a fictitious date of May 27, 2012 for when the bikeshare system opens, which is exactly one-year prior to the date it actually began operation. $BikeOpen_t$ is then an indicator if the date is on or after May 27, 2012. If the common trends assumption holds, we would expect to find no effect in this model.
Alternate Specification Using Fare Type

One potential problem with a difference-in-differences analysis is that factors unrelated to the opening of the bikesharing system occurring at the same time that affect the control and treatment groups in different ways could bias the results. Some examples could be land use, demographic, or economic changes that occur around the same time that bikesharing opens and that impact bus ridership in lower Manhattan and downtown Brooklyn differently than in other areas of those boroughs. Another potential concern is if the bikesharing system was implemented based on pre-existing differences in outcomes. For example, we would be concerned if the bikesharing station locations were chosen with the intent to reduce bus passenger congestion. We find no evidence of this in the planning documents. Furthermore, the majority of the control area was planned for inclusion in the bikesharing system; it was only a matter of when the subsequent phases were rolled out. That means that the control and treatment areas at least met minimum density and feasibility requirements, and so are comparable across those characteristics (New York City Department of City Planning, 2009). We acknowledge that, from a methodological perspective, this is not as good as if the treated areas were randomly assigned and therefore, we test an alternative control and treatment.

To address these concerns about the endogeneity of the intervention itself and because we cannot control for some potential omitted variables, we use a different control and treatment group based on MetroCard type. Reduced fare MetroCards are available to riders who are 65 years of age or older or who have a qualifying disability. In the bikesharing trip data, we have information on the biker’s age for most (89%) of the 13,118,401
trips taken during the study period. We find that only 1.19% of these bike trips were taken by persons age 65 or older\textsuperscript{11}. Most people who qualify for a reduced fare MetroCard due to disability are also unlikely to be bikeshare users. Although we do not have exact statistics on the proportion of people who have a qualifying disability who use bikeshare, in the latest New York Metropolitan regional travel survey, persons with disabilities report biking only 1.5% of the time compared to other travel modes (New York Metropolitan Transportation Council and North Jersey Transportation Planning Authority, 2014). Furthermore, many of the physical and mental disabilities that qualify someone for a reduced fare MetroCard would likely prohibit him or her from riding a traditional bicycle\textsuperscript{12} (MTA New York City Transit, 2015). Because there is very little overlap in terms of age and because many of the qualifying disabilities are likely to prevent the person from using bikesharing, we use reduced fare bus ridership as an alternative control group and compare it to full fare bus ridership as the treatment group.

Looking at different groups of passengers on the same bus route alleviates the concern that bus routes that are near bikesharing stations are intrinsically different from routes that are not near bikesharing stations or that bikesharing station locations were chosen precisely because they would have a different impact on bus transit. Two groups of passengers on the same bus route would be exposed to the same demographic, land use, economic, and other location-based changes that we are unable to control for in the main specification. In this specification, we only include bus routes that are within the bike-

\textsuperscript{11}We exclude observations where the rider was listed as being older than 105 years old.

\textsuperscript{12}A qualifying disability includes a serious mental illness for which the individual is receiving Supplemental Security Income benefits, a hearing impairment, an ambulatory disability, loss of both hands, mental retardation and/or other organic mental capacity impairment, or applies to someone who is receiving Medicare benefits for any reason other than age.
sharing area, which was defined previously as routes that have at least one bikesharing
dock within 0.25 miles of the bus route.

In this specification, we use the following regression equation:

\[
\ln(\text{BusRiders}_{kjt}) = \alpha + \beta \text{BikeOpen}_t \times \text{FullFare}_k \times \text{Docks}_j + \\
\delta \text{DateFE}_t + \theta \text{FullFare}_k \times \text{RouteFE}_j + \lambda \text{Controls}'_{kjt} + \epsilon_{kjt} \quad (2.3)
\]

where \( \ln(\text{BusRiders}_{kjt}) \) is the natural log of ridership for passenger type \( k \) on day \( t \) on bus route \( j \). We use daily unlinked bus trips per route by fare type. \( \text{FullFare}_k \) is an indicator for fare type, and it is 1 for full fare bus trips and 0 for reduced fare bus trips. Our variable of interest is \( \text{BikeOpen}_t \times \text{FullFare}_k \times \text{Docks}_j \), which identifies the treated group of passengers after the bikesharing system opened and is weighted by the number of bike docks (in thousands) near the bus route to take treatment intensity into account. We include date fixed effects again and add route fixed effects by fare type \( (\text{FullFare}_k \times \text{RouteFE}_j) \). We use the same set of control variables, including scheduled revenue miles of bus service, the introduction of Select Bus Service, the roll out of real-time bus information, and changes to the taxi service area. We also control for the introduction of the Access-A-Ride MetroCard program, which provides paratransit customers with a MetroCard eligible for up to four free trips per day. The program was rolled out over an 18-month period, with the first round of MetroCards distributed in April 2013. We control for this using a dummy variable for reduced fare passengers on or after April 15, 2013. We also try a specification including a linear time trend by fare type and perform a placebo analysis.
Figure 2.7: Average Daily Bus Ridership By Month in Manhattan and Brooklyn for Alternative Treatment Based on Fare Type

<table>
<thead>
<tr>
<th>Unlinked Bus Trips By Fare Type</th>
<th>Pre (354 days)</th>
<th>Post (365 days)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Min.</td>
</tr>
<tr>
<td>Manhattan and Brooklyn (45 routes)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reduced Fare (Control) (n=45)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Daily Route-Level</td>
<td>1,972</td>
<td>11</td>
</tr>
<tr>
<td>Daily Total</td>
<td>82,267</td>
<td>26,667</td>
</tr>
<tr>
<td>Full Fare (Treatment) (n=45)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Daily Route-Level</td>
<td>10,343</td>
<td>51</td>
</tr>
<tr>
<td>Daily Total</td>
<td>431,422</td>
<td>139,950</td>
</tr>
<tr>
<td>Manhattan (23 routes)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reduced Fare (Control) (n=23)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Daily Route-Level</td>
<td>2,469</td>
<td>24</td>
</tr>
<tr>
<td>Daily Total</td>
<td>55,551</td>
<td>18,755</td>
</tr>
<tr>
<td>Full Fare (Treatment) (n=23)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Daily Route-Level</td>
<td>10,502</td>
<td>78</td>
</tr>
<tr>
<td>Daily Total</td>
<td>236,330</td>
<td>69,537</td>
</tr>
</tbody>
</table>

Figure 2.7 shows each month’s daily average route-level full fare and reduced fare bus ridership. The accompanying table provides descriptive statistics for the daily route-level data by borough and control and treatment groups. The two groups follow similar trends
prior to the opening of the bikesharing system, although the variation is more pronounced for full fare ridership. Additionally, there is a drop in full fare ridership compared to reduced fare ridership around the time the bikesharing system opened.

2.6 Results

Overall, the results indicate a significant decrease in bus ridership coincident with the implementation of the bikesharing system in New York City. We find a significant decrease in daily bus ridership along routes that are near bikesharing in comparison to routes that are not. This relationship holds whether or not we control for bike lane infrastructure and is significant for Manhattan and Brooklyn and for Manhattan alone. The result is robust to including a treatment-specific time trend and to varying the method of measuring treatment intensity. Moreover, there is not a significant effect in the placebo model, which further supports our findings. Results from the alternative control and treatment group based on fare type confirm the main findings.

Results Using Geographic Coverage of Bikesharing

Column 1 of Table 2.1 shows the results for the main specification using treatment intensity of docks for bus routes in Manhattan and Brooklyn. In this case, every thousand bikesharing docks along the bus route is associated with a 0.0245 reduction in the natural log of daily unlinked bus trips, or equivalently a 2.42% reduction in unlinked trips (using the equation: \(100 \cdot [e^\beta - 1]\)). This result is significant at the 0.1 percent level. For Manhattan and Brooklyn the mean number of bikesharing docks near bus stops along a treated
<table>
<thead>
<tr>
<th></th>
<th>Manhattan &amp; Brooklyn</th>
<th>Manhattan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Bikeshare area indicator</td>
<td>-0.0245***</td>
<td>0.0170***</td>
</tr>
<tr>
<td>Bikeshare area indicator</td>
<td>(0.0038)</td>
<td>(0.0047)</td>
</tr>
<tr>
<td>open indicator × Docks (in thousands)</td>
<td>0.9914***</td>
<td>0.9876***</td>
</tr>
<tr>
<td>Scheduled revenue miles (ln)</td>
<td>(0.0824)</td>
<td>(0.0830)</td>
</tr>
<tr>
<td>Boro Taxi indicator</td>
<td>0.0119</td>
<td>0.0143</td>
</tr>
<tr>
<td></td>
<td>(0.0113)</td>
<td>(0.0119)</td>
</tr>
<tr>
<td>Select Bus Service indicator</td>
<td>-0.1049***</td>
<td>-0.1098***</td>
</tr>
<tr>
<td></td>
<td>(0.0110)</td>
<td>(0.0091)</td>
</tr>
<tr>
<td>Bus Time indicator</td>
<td>0.0044</td>
<td>0.0050</td>
</tr>
<tr>
<td></td>
<td>(0.0094)</td>
<td>(0.0093)</td>
</tr>
<tr>
<td>Bike lanes within 0.25 mi of bus route (in miles)</td>
<td>-0.0075**</td>
<td>-0.0083**</td>
</tr>
<tr>
<td>Time trend × Bikeshare area indicator</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.8002***</td>
<td>1.9110***</td>
</tr>
<tr>
<td></td>
<td>(0.5407)</td>
<td>(0.5440)</td>
</tr>
<tr>
<td>Date fixed effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Route fixed effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>58851</td>
<td>58851</td>
</tr>
<tr>
<td>Routes</td>
<td>85</td>
<td>85</td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001

Note: The dependent variable for each regression is the natural log of daily unlinked bus trips. Bootstrap standard errors (500 replications) clustered at the bus route level are presented in parenthesis.
route is 1,359. For a treated route with the mean number of docks, this is equivalent to a 3.3% reduction in unlinked bus trips. We estimated the percent effect using the mean number of thousands of docks and the equation: \(100 \cdot \left(e^\beta - 1\right) \cdot \text{docks}.\) Total average daily unlinked bus trips on treated routes in Manhattan and Brooklyn during our study period prior to bikeshare opening was 548,580. A 3.3% decrease equates to a fall in ridership of approximately 18,100 unlinked bus trips per day.

In column 5 of Table 2.1, the results for Manhattan alone show that every thousand bikesharing docks along the bus route is associated with a 0.0325 reduction in the natural log of unlinked bus trips, or 3.20% of trips, and this result is also significant at the 0.1 percent level. This is equivalent to a 6.4% reduction in bus trips on a route with the mean number of docks, which is 2,002 for Manhattan alone. Average daily trips on treated routes in Manhattan prior to bikeshare opening was 305,439, so this represents a fall in ridership of approximately 19,500 trips per day. Not surprisingly, the results are slightly larger in the Manhattan specification where more bikesharing infrastructure is located, but the error bounds are larger as there are fewer bus routes in the sample. We also vary the time period and level of temporal aggregation and still find a significant fall in bus ridership (not shown). Specifically, when we include the 2-month adjustment period (using the 12-months before and after bikesharing opened), the result is smaller and when we exclude all of 2013 (using 2012 and 2014), the result is larger. Furthermore, when we use the same time period as the main specification, but aggregate to monthly-level data, we again find a significant effect that is slightly smaller.

We also tried separating the effect of the bikesharing infrastructure from the effect of investing in additional bike lanes during this time by including the miles of bike lanes
within 0.25 miles of each bus route over time as a control variable. As shown in columns 2 and 6 of Table 2.1, when we include bike lanes, the effect is slightly smaller (coefficient of -0.0170 versus -0.0245 in Manhattan and Brooklyn; -0.0262 versus -0.0325 in Manhattan alone), but the result remains significant and negative. This is a fall in bus ridership of 1.69% per thousand bikesharing docks and 2.3% for a route with the mean number of docks, which equates to 12,600 fewer daily unlinked bus trips in Manhattan and Brooklyn. In Manhattan, there is a fall in bus ridership of 2.59% per thousand bikesharing docks, which is a fall of 5.2% on the mean route, representing 15,800 fewer daily bus trips in Manhattan. As explained in Section 2.5, because bike lanes is a confounding variable (and in fact the correlation between these regression coefficients is -0.47 for Manhattan and Brooklyn and -0.57 for Manhattan), this is not our preferred specification, but it does indicate two things. First, installing both the bikesharing system with the supporting bike lane infrastructure is likely to have had a bigger impact on treated routes. Second, this indicates that cycling infrastructure alone is unlikely driving the main result. However, we recommend future research consider untangling these effects.

In another check of the main specification, we control for a linear time trend in bus ridership by treatment area, and this is shown in columns 3 and 7 of Table 2.1. We find that the bikesharing effect is similar in magnitude and still significant. Specifically, in Manhattan and Brooklyn (column 3), the coefficient of -0.0282 implies that every thousand bikesharing docks near the bus route is associated with a 2.78% reduction in unlinked bus trips (compared to a 2.42% reduction without the time trend). This is equivalent to a reduction in bus trips on a route with the mean number of bikesharing docks of 3.8% or roughly 20,800 daily bus trips in Manhattan and Brooklyn. For Manhattan only (column
7), the results are equivalent to a 4.6% reduction in bus trips on a route with the mean number of bikesharing docks, which equates to approximately 14,000 fewer total daily unlinked bus trips. The results are similar in the specifications controlling for the miles of bike lanes (shown in columns 4 and 8 of Table 2.1). Additionally, the results are similar using a quadratic instead of a linear time trend (not shown).

As can be seen in Table 2.1, the control variables have the expected sign and magnitude. The coefficient on scheduled revenue miles, which is typically an important predictor of bus ridership, is large and significant. Bus Time real-time information is positive and sometimes significant, which generally aligns with previous findings (Brakewood, Macfarlane, and Watkins, 2015).

Table 2.2: Results Using Alternative Treatment Measures

<table>
<thead>
<tr>
<th></th>
<th>Manhattan &amp; Brooklyn</th>
<th>Manhattan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Dummy Station</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bikeshare area indicator</td>
<td>-0.0166</td>
<td>(0.0131)</td>
</tr>
<tr>
<td>Bikeshare open indicator</td>
<td>-0.0869***</td>
<td>(0.0145)</td>
</tr>
<tr>
<td>Bikeshare area indicator</td>
<td>-0.0038*</td>
<td>(0.0018)</td>
</tr>
<tr>
<td>Bikeshare open indicator</td>
<td>1.8282***</td>
<td>(0.5384)</td>
</tr>
<tr>
<td>Bikeshare open indicator</td>
<td>1.8212***</td>
<td>(0.5381)</td>
</tr>
<tr>
<td>Bikeshare open indicator</td>
<td>0.8259</td>
<td>(0.7162)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.8282***</td>
<td>(0.5384)</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Date fixed effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Route fixed effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>58851</td>
<td>58851</td>
</tr>
<tr>
<td>Routes</td>
<td>85</td>
<td>85</td>
</tr>
</tbody>
</table>

Note: The dependent variable for each regression is the natural log of daily unlinked bus trips. Bootstrap standard errors (500 replications) clustered at the bus route level are presented in parenthesis. Scheduled revenue miles (ln), Boro Taxi indicator, Select Bus Service indicator, and Bus Time indicator are used as control variables, but not displayed in the table.

In Table 2.2, we show the results using other measures of treatment intensity. The results are consistent in sign and approximate magnitude with our main findings no matter
which treatment definition is used, although we do not find a significant result using a dummy variable for Manhattan and Brooklyn (column 1). When we measure bikeshare treatment as a dummy variable for Manhattan (column 4), we find that routes near at least one bikesharing station have a 6.4% decrease in unlinked bus trips. In columns 2 and 5, we find that every hundred bikesharing stations along a route is associated with a 8.32% reduction in unlinked bus trips in Manhattan and Brooklyn, and a 11.55% reduction in Manhattan. Taking the mean number of stations, these estimates are very similar in magnitude to the main specification. Finally, when we measure bikeshare treatment based on the number of bikeshare trips originating near the bus route we find a smaller impact, although as noted in Section 2.5, infrastructure-based measures are more appropriate given our methodology.

Table 2.3: Results for Placebo Analysis for Treatment Based on Geographic Coverage

<table>
<thead>
<tr>
<th></th>
<th>Manhattan &amp; Brooklyn (1)</th>
<th>Manhattan (2) Placebo</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bikeshare area indicator × Placebo date indicator × Docks (in thousands)</td>
<td>-0.0184 (0.0216)</td>
<td>-0.0027 (0.0267)</td>
</tr>
<tr>
<td>Scheduled revenue miles (ln)</td>
<td>1.0202*** (0.0916)</td>
<td>1.1628*** (0.1170)</td>
</tr>
<tr>
<td>Select Bus Service indicator</td>
<td>-0.0329*** (0.0070)</td>
<td>-0.0327* (0.0154)</td>
</tr>
<tr>
<td>Bus Time indicator</td>
<td>0.0022 (0.0064)</td>
<td>0.0161 (0.0157)</td>
</tr>
<tr>
<td>Constant</td>
<td>2.0676*** (0.6456)</td>
<td>1.2364 (0.8262)</td>
</tr>
<tr>
<td>Date fixed effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Route fixed effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>57317</td>
<td>23783</td>
</tr>
<tr>
<td>Routes</td>
<td>82</td>
<td>34</td>
</tr>
</tbody>
</table>

* p < 0.05, ** p < 0.01, *** p < 0.001

Note: The dependent variable for each regression is the natural log of daily unlinked bus trips. This specification uses a time period shifted one year earlier than the main specification (from May 27, 2011 to May 26, 2013) with a fake start date for bikesharing of May 27, 2012, exactly one year prior to the actual start date. Bootstrap standard errors (500 replications) clustered at the bus route level are presented in parenthesis. The Boro Taxi indicator is not included in these models because it had not yet begun.
Additionally, we demonstrate that these findings are unlikely the result of a placebo effect. In the placebo model, where we used a fictitious start date for bikesharing (exactly one year prior to actual opening), we do not find a significant effect in either the Manhattan and Brooklyn or the Manhattan only specifications. These results are shown in Table 2.3 and suggest that the result is indeed zero when an effect should not exist. There is also no placebo effect in any of the variations including the linear time trend by treatment or controlling for bike lanes.

Finally, we performed a number of other analyses that yielded similar results and are therefore not shown here. We ran a model with total daily unlinked bus trips as the dependent variable instead of the natural log and found almost the same fall in ridership, although some of these results were less significant. Because difference-in-differences can be sensitive to functional form and because average daily route-level ridership in our treatment is larger than the control, we prefer the specification using the natural log of ridership. In other analyses, we changed the size of the catchment area around bus stops to a half mile or to a tenth of a mile and counted the number of bikesharing docks in this radius. The results were similar to our main specification using a quarter mile catchment area.

Results for Alternative Treatment Based on Fare Type

In the analysis using full fare ridership as the treatment group and reduced fare ridership as the control group, we also find a significant decrease in bus ridership. In column 1 of Table 2.4, the results for Manhattan and Brooklyn show that every thousand bikesharing
Table 2.4: Alternate Analysis With Treatment Based on Fare Type

<table>
<thead>
<tr>
<th></th>
<th>Manhattan &amp; Brooklyn</th>
<th>Manhattan</th>
<th>Manhattan</th>
<th>Manhattan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) ByFareType</td>
<td>(2) ByFareType w/TimeTrend</td>
<td>(3) ByFareType</td>
<td>(4) ByFareType w/TimeTrend</td>
</tr>
<tr>
<td>Full fare indicator × Bikeshare open indicator × Docks (in thousands)</td>
<td>-0.0318***</td>
<td>-0.0350***</td>
<td>-0.0206***</td>
<td>-0.0232***</td>
</tr>
<tr>
<td></td>
<td>(0.0076)</td>
<td>(0.0082)</td>
<td>(0.0049)</td>
<td>(0.0054)</td>
</tr>
<tr>
<td>Access-A-Ride MetroCard indicator</td>
<td>0.0005</td>
<td>0.0388***</td>
<td>0.0100</td>
<td>0.0326***</td>
</tr>
<tr>
<td></td>
<td>(0.0107)</td>
<td>(0.0082)</td>
<td>(0.0098)</td>
<td>(0.0073)</td>
</tr>
<tr>
<td>Scheduled revenue miles (ln)</td>
<td>0.9570***</td>
<td>0.9574***</td>
<td>1.0617***</td>
<td>1.0619***</td>
</tr>
<tr>
<td></td>
<td>(0.1065)</td>
<td>(0.1065)</td>
<td>(0.1238)</td>
<td>(0.1236)</td>
</tr>
<tr>
<td>Boro Taxi indicator</td>
<td>0.0179</td>
<td>0.0177</td>
<td>-0.0178</td>
<td>-0.0168</td>
</tr>
<tr>
<td></td>
<td>(0.0185)</td>
<td>(0.0184)</td>
<td>(0.0186)</td>
<td>(0.0184)</td>
</tr>
<tr>
<td>Select Bus Service indicator</td>
<td>-0.0731***</td>
<td>-0.0743***</td>
<td>-0.0001***</td>
<td>-0.0001***</td>
</tr>
<tr>
<td></td>
<td>(0.0124)</td>
<td>(0.0125)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Bus Time indicator</td>
<td>0.0138</td>
<td>0.0150</td>
<td>-0.0178</td>
<td>-0.0168</td>
</tr>
<tr>
<td></td>
<td>(0.0142)</td>
<td>(0.0143)</td>
<td>(0.0186)</td>
<td>(0.0184)</td>
</tr>
<tr>
<td>Time trend × Full fare indicator</td>
<td>0.0001***</td>
<td>0.0001***</td>
<td>0.0001***</td>
<td>0.0001***</td>
</tr>
<tr>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Constant</td>
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<td>0.9740</td>
<td>0.5725</td>
<td>0.5588</td>
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<td></td>
<td>(0.7081)</td>
<td>(0.7077)</td>
<td>(0.8162)</td>
<td>(0.8137)</td>
</tr>
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<td>Date fixed effects</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Route × Full fare fixed effects</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
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<td>61466</td>
<td>32566</td>
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<tr>
<td>Routes</td>
<td>45</td>
<td>45</td>
<td>23</td>
<td>23</td>
</tr>
</tbody>
</table>

* p < 0.05, ** p < 0.01, *** p < 0.001

Note: The dependent variable for each regression is the natural log of daily unlinked bus trips. Bootstrap standard errors (500 replications) clustered at the bus route level are presented in parenthesis. The Bus Time and Select Bus Service indicators are excluded from the Manhattan specification because they did not change in the sample during this time.

docks along the bus route is associated with a 0.0318 reduction in the natural log of full fare unlinked bus trips, or 3.13% of full fare trips, and this result is also significant at the 0.1 percent level. This is equivalent to a 4.2% reduction in full fare trips on a route with the mean number of docks. Average daily full fare trips on treated routes in Manhattan prior to bikeshare opening was 431,422, so this represents a fall in ridership of approximately 18,300 full fare trips per day. For Manhattan only, shown in column 3, the results are smaller. In this case, there is a 2.04% fall in full fare trips per thousand docks along the route, which is equivalent to a 4.1% reduction in full fare trips on a route with the mean number of docks. Using average daily full fare trips in Manhattan of 236,330, this represents a fall in ridership of approximately 9,670 full fare trips per day. When we
account for a linear time trend by treatment group (in columns 2 and 4), the estimated reduction in bus ridership remains significant and is larger. A placebo test (not shown) is not significant in any of these variations.

Discussion of Results

Through a number of specifications and tests, we find evidence that bikesharing reduced bus ridership in New York City. We included potential omitted variables such as changes to scheduled revenue miles of service and the introduction of Select Bus Service, Bus Time, and Boro Taxis, tried a specification with a linear time trend by treatment, used alternate treatment measures, and performed a placebo test. Because each of these supported our main findings, it is unlikely that the result is being driven by some general trend in the treatment group. Also, limiting the sample to only bus routes that were within the bikesharing area and reproducing the result using an alternative control and treatment group by fare type demonstrates that it is unlikely that the results are being driven by something intrinsic only to the areas that received bikesharing. We discuss limitations of our findings in the following section.

We presented the main specification side-by-side a specification controlling for bike lane infrastructure. Methodologically it is difficult to separate the effect of opening the bikesharing system from other actions the city was taking at this time to support bicycling, such as expanding bike lanes as discussed in Section 2.5. In terms of policy and planning applications, separating these effects may be less useful because in practice, municipal investment more broadly in bicycling often goes hand-in-hand with opening a bikesharing
system. Our main specification could potentially be interpreted as capturing this net
effect; however, future research to disentangle these related factors is recommended.

A final note is that, although we find that the immediate impact of bikesharing is a
decline in daily bus ridership, this may not reflect the long-term impact. As pointed out by
Singleton and Clifton, (2015), even if transit and cycling are short-term substitutes, they
could act as complements in the long-term. A transportation network based on a robust
transit system and cycling network could impact future travel behavior, particularly long-
term factors like the decision to own a car, which is not captured here.

2.7  Areas for Improvement and Future Research

There are many areas for improvement and future research that have emerged from this
study. First, a challenging aspect of this research design is controlling for all of the fac-
tors that could have affected route-level daily bus ridership during the study period. For
example, changes in land use, population, economic activity, fares, subway service, and
unscheduled changes in bus service were not included in our models. If such changes had
an unequal effect in the treatment and control areas during the study period and if full
fare passengers were more sensitive to these changes than reduced fare passengers, then
their impact on bus ridership is not captured in our models and is an important area for
improvement and future research.

Another factor that we do not specifically control for is the growth of new ridehailing
services that were made available throughout New York City during the study period.
Because ridehailing data are not available prior to the opening of the bikesharing system,
we cannot explicitly control for it in our models. However, if new ridehailing services impact bus ridership similarly within the control and treatment areas, then this has been accounted for in our main specification. If ridehailing has an uneven impact in these two areas of the city but has the same impact across full fare and reduced fare riders, then we would expect to find a large discrepancy between the main specification and the alternative treatment using fare type, which we do not. Furthermore, if ridehailing has a different impact across the areas but follows a linear growth trend, then it could already be captured in the model that includes a time trend by treatment area. While we have utilized these strategies in an attempt to capture the impacts of ridehailing on bus ridership, we believe that this is an important area for future study, particularly in light of emerging ridehailing data availability.

Important areas for future research that have emerged from this work, include studying other impacts that bikesharing systems could have on bus systems and on the transit system more broadly. First, reductions in bus ridership associated with the availability of bikesharing could have caused decreases in bus operating costs or revenue from bus passenger fares; this could have positive or negative implications for the transit agency and should be explored further. Similarly, reductions in bus ridership during peak hours could result in decreased crowding on some of the most heavily trafficked bus routes in New York City, which could improve the quality of service from the passenger perspective. Furthermore, as more travelers choose to bike using either bikesharing or personal bicycles, there could be impacts on the operations of vehicles on local roadways, including buses, due to the lower travel speeds of non-motorized modes. Therefore, empirical investigation of the relationship between bus and bicycle speeds is recommended. Each of
these could have redistributive impacts and equity implications that have yet to be studied. Future research should also quantify the impact of bikesharing on subway ridership in New York City. Because the subway travels at different speeds and has larger distances between stops, it is unlikely to have the same relationship with bikesharing as the bus system. Additionally, because New York City has a much denser bikesharing system and a more heavily used bus system, future research should also study the relationship between bus and bikeshare in small and medium sized cities.

Finally, the broader planning and public policy implications of this research should be considered. If both buses and bikes are considered shared transportation modes, questions of finance and subsidies will naturally be raised. In particular, our findings could suggest different arrangements for public-private partnership in which the impacts to municipal transit agencies are included.

2.8 Policy Implications and Conclusion

In this study, we quantified the effect that opening a bikesharing system has on bus ridership by exploiting a natural experiment afforded by the phased implementation of bikesharing in areas of New York City. The results indicate a significant decrease in bus ridership coincident with the implementation of the bikesharing system. Our preferred model suggests that every thousand bikesharing docks along a bus route is associated with a 2.42% reduction in daily unlinked bus trips on routes in Manhattan and Brooklyn. This represents a total daily fall in bus ridership of approximately 18,100. In the second model that additionally controls for bike lane infrastructure during this time, we find a
smaller reduction due to bikesharing of 1.69%, or approximately 12,600 fewer daily bus trips. Based on both model results, the overall ridership impacts were surprisingly large. Considering that total average daily bikeshare trips are approximately 26,000 during the study period, our estimates of a decrease of 18,100 or 12,600 daily unlinked bus trips are sizable. If this effect is driven entirely by direct modal substitution of bikeshare members, then, even in the case where we separately control for bike lane infrastructure, it would mean that close to 50% of trips now made by bikeshare were previously made by bus. The model without bike lanes suggests that approximately 70% of bikeshare members may be substituting bikeshare for bus use. These percentages are higher than has been found in surveys of bikeshare members in other cities (Shaheen, Martin, and Cohen, 2013). Previous research suggests that the denser the bikesharing network and the denser the urban form, the more bikeshare members substitute biking for public transit (Martin and Shaheen, 2014). At the time of this writing, New York City’s bikesharing system is denser than the North American cities previously surveyed, so it is not surprising that it is in the higher end of estimates. However, this proportion of modal substitution is so large that we speculate that a considerable portion of the fall in bus ridership comes from an impact on non-members of bikeshare. It could be that people who are not bikeshare members have increased private cycling trips in lieu of bus trips. Because our results indicate that the effect could be substantial, we recommend further study to investigate how bikesharing systems influence the travel behavior of non-members.

Finally, having a negative impact on bus ridership should not be a deterrent to implementing or expanding bikeshare schemes. In fact, the number of people who use bikesharing in New York City is a testament to its success at increasing urban mobil-
ity. Instead, the knowledge of how these systems are interrelated is vital for planning a mutually reinforcing sustainable transport network. By quantifying the net effect of bike-sharing, we hope our findings provide planners and policymakers with more information on which to base future planning decisions to facilitate coordination of multimodal transportation. We hope that a better understanding of the relationship between these two different modes encourages agencies who traditionally operate separately to create more integrated systems that support the reality of multimodal, shared transportation systems.
Chapter 3

Accessibility and Mobility in Nairobi

This work was developed in collaboration with Dr. James Rising (University of California, Berkeley), Dr. Jacqueline Klopp (Columbia University), and J Mwikali Mbilo (University of Nairobi).

3.1 Introduction

A key goal of urban transportation planning is to provide people with access to a greater number of opportunities and interactions with other people and places, a goal which supports the creative dynamics, liveability, and productivity of cities (Sclar and Lönnroth, 2014; UN Habitat, 2013). The concept of accessibility based on this insight has been used in transportation planning since Hansen, (1959) and a number of accessibility measures have been developed to evaluate how well people can access the places, opportunities, and services they need (El-Geneidy and Levinson, 2006; Geurs and Wee, 2004; Handy and Niemeier, 1997; Wee, 2016; Weibull, 1980). Elevating the concept of systemic access, whereby accessibility becomes the objective of urban governance, and developing the funding tools to support it may promote economic, social, and environmental goals (Dodson et al., 2016; Sclar and Lönnroth, 2016). Yet, in many cities across the globe transportation planning focuses primarily on increasing travel speeds and reducing congestion.
In Africa where many cities are growing very rapidly, this appears to be the case (Hagans, 2013; Porter, 2016), perhaps contributing to the fragmentation, disconnection, and high costs of living in these cities (Lall, Henderson, and Venables, 2017). Reinforcing this problematic trend, land use and transport data are limited for these cities, and this contributes to the paucity of accessibility studies (Cervero, 2013). Lack of data, metrics and analysis hinders the integration of the concept of access into the transportation planning process just as many new and useful tools are being developed (Páez et al., 2013; Qu et al., 2016; Stewart and Zegras, 2015).

Nairobi, Kenya is a clear case where mobility - a narrow focus on increasing speeds, reducing travel time, and on other physical characteristics of the transport system - tends to dominate transportation planning compared to concerns with accessibility (Hagans, 2013; Klopp, 2012). With a poor and fragmented road network, much focus in Nairobi is on building and expanding roads and highways as a way to reduce congestion. Yet how these projects actually impact the high levels of fragmentation and social and spatial inequality as well as accessibility in the city is unexplored (Hagans, 2013; Lall, Henderson, and Venables, 2017; UN Habitat, 2016).

It is particularly important to do contextually sensitive accessibility studies in cities like Nairobi, because these cites have quite different challenges from the more automobile-centric cities that have typically been studied in the US and Europe. One crucial difference is that instead of a minority who experience transport and income poverty, in these cities transport disadvantage is a reality for the majority of the population (Lucas, 2011). Another key difference is that, a critical part of transport in these cities consists of minibus systems known as paratransit that are privately owned, and run on flexible schedules,
stops, and sometimes routes (Behrens, McCormick, and Mfinanga, 2016; Cervero, 2000). Little is known about the ability of these systems to provide for increased accessibility citywide, because while paratransit systems can meet unmet demand they also tend to oversupply service in the city center, contributing to congestion (Allaire, Ferro, and Abeiku, 2016). In Nairobi, over 80% of all trips are taken by paratransit or by walking (Nairobi City County, 2014a). Automobile use is limited but prevalent among the middle and upper classes. As a result, metrics based solely on driving, as often happens in the literature, capture only a small portion of the overall level of accessibility and exclude consideration of accessibility for the majority of citizens.

In an effort to address theses gaps in what we know about accessibility in the rapidly growing cities of lower income countries in Africa, Asia, and Latin America, this research draws on data for Nairobi to test two different metrics which explore the relationship between transportation, urban location, and residence. We use available transport, health care, and residential data, to calculate cumulative opportunities measures over a grid across Nairobi. In one metric, which we refer to as the mobility measure, we focus on how the different transport modes enable travel to other locations throughout the city. We develop a methodology for exploring mobility depending on which mode is used: walking, paratransit, or driving. Given that the poorest depend most on walking, the lower middle classes take paratransit, and the wealthy tend to drive, this gives a rough idea of inequality in physical access across socio-economic categories. In the second metric, which we refer to as the accessibility measure, we incorporate the location of health care facilities and examine the relationship between residential typology, a proxy for socio-economic status, and access to these facilities.
Highlighting the importance of understanding the interaction between transport and land use, we find that the paratransit system does comparatively better in the accessibility measure than the mobility measure. Our results show, unsurprisingly, that driving provides the highest accessibility and walking the lowest, and that accessibility decreases with distance from the Central Business District (CBD). We order seven residential typologies from low to high, based on median income. For the same distance from the CBD, we find rather interestingly that lower residential types have higher walking and paratransit accessibility than higher residential types. The highest residential type also has the lowest driving accessibility, reflecting Nairobi’s long history of social segregation and the tendency of the rich to live in secluded areas farther from the CBD. Further, the poor tend to cluster near the CBD where they have better accessibility to jobs and services. Any effort to remove them from these locations could clearly cause harm because of the huge advantage in access that these locations provide.

Traffic congestion, a constant concern in Nairobi is no doubt linked in part to this residential structure and efforts to build out of this congestion by road expansion are unlikely to solve the problem as we have discovered in other parts of the world (Duranton and Turner, 2011). In addition, it is unlikely that current automobile and mobility-centric transportation planning will address the overall problems of social segregation and exclusion that contribute to poor overall accessibility for the lower and middle classes. To improve accessibility for the majority, stronger efforts would need to focus on building better, affordable, more extensive and high quality public transport and supporting mixed land use including in wealthier neighborhoods to reduce the need to drive. Overall, this work emphasizes the importance of developing metrics, conducting accessibility analysis,
and integrating this work into transportation planning in African cities.

3.2 Prior Research on Accessibility in Low Income Countries

Accessibility can be defined and operationalized in a number of different ways. We adopt the commonly used definition of accessibility as the potential of opportunities for interaction (Hansen, 1959) and focus on location-based measures. Location-based measures can be thought of as showing the potential access to destinations an individual has at a given location (Geurs and Wee, 2004; Handy and Niemeier, 1997). This is an important distinction because these measures do not capture actual travel behavior or account for varied constraints that are unique to individuals including, for example, affordability and physical access for the disabled (Weber, 2006). For this study, the focus is on demonstrating the variation in the provision of transport and land-use access across residential types so location-based measures are appropriate. We discuss limitations and future research into travel behavior in Section 3.5.

A number of empirical studies have looked at accessibility and social disparity in cities in North America. A large portion of this research focuses on access to jobs by car or transit or both with some studies explicitly taking into account barriers such as car ownership or transit fares (El-Geneidy et al., 2016b; Foth, Manaugh, and El-Geneidy, 2013; Grengs, 2010; Hess, 2005; Shen, 1998, 2001). These studies find that, contrary to spatial mismatch theories, socially disadvantaged groups living in inner city neighborhoods often have
higher levels of access to jobs. Many point out that car ownership or the ability to pay transit fares is an important prerequisite that, when lacking can offset the advantages of being centrally located. In fact, Grengs’ analysis shows that, for people who do not own a car, the inner city is the only location that provides any level of job accessibility for them (Grengs, 2012). He finds that some groups are extremely disadvantaged due to low car ownership rates and poor transit service rather than by their location. Looking at access to jobs is relevant because transit-based jobs accessibility has been linked to the employment outcomes (Kawabata, 2003), but access to other opportunities is also a factor in social equity. Studies that have looked at other types of destinations have found that, in most cases, socially disadvantaged groups do not experience lower levels of non-work accessibility, although there are exceptions (Grengs, 2015; Scott and Horner, 2008). These studies demonstrate that accessibility measures can be a useful way to study social disadvantage and urban structure, although it is unclear how well these findings apply to low-income cities.

Travel surveys and focus groups reveal much about transport, land use, and social exclusion in Sub-Saharan Africa, by demonstrating how residential location can limit the opportunities available to low-income households. In a study in the Tshwane region of South Africa, an urban area similar to Nairobi in terms of poverty and paratransit use, Lucas, (2011) explores transport disadvantage through the lens of social exclusion. Using qualitative analysis of a series of focus groups, she finds that lack of transport and cost is a considerable problem for low-income households and that it limits their ability to access key activities including employment, education, health services, and social networks. This prevents them from fully participating in society and leads to social exclusion (Páez et al.,
In a study of the eThekwini Metropolitan Area in South Africa, Venter, Vokolkova, and Michalek, (2007) analyzed travel surveys and found that households living further from the central business district (CBD) faced higher travel burdens including longer distances, higher costs, and lack of public transport, but that distance from the CBD was not the only factor. Notably, the neighborhood that was furthest from the CBD in their study had better access and mobility than ones that were located closer. This neighborhood had the benefit of a mix of amenities within walking distance including informal work opportunities, social activities, and health services.

Overall, a limited number of studies using accessibility measures exist for African cities. Melbye et al., (2015) focus on how the spatial structure and road network in Dar es Salaam generate congestion which, in turn, affect road accessibility of motorized vehicles. Another study of Dar es Salaam suggests that the spatial structure and transportation networks in the city prevent the development of social capital from contributing to social exclusion (Olvera, Plat, and Pochet, 2003). In Accra, Moller-Jensen, Kofie, and Allotey, (2012) map accessibility by time of day and at different directions, incorporating congestion levels and traffic flows. In a report for the Gauteng City-Region in South Africa, Gotz et al., (2014) studies both the relationship between residential typology and travel patterns, as well as uses a gravity measure to capture access to jobs. The report highlights the advantages that centrally located households have in terms of access to public transport, lower costs, and shorter travel distances, as well as the lack of local amenities in peripheral locations. Their results, using an accessibility measure for a subset of townships, show that low access to jobs is a combination of peripheral location, lack of transit access, and few economic opportunities nearby. Additional work in Nairobi has
calculated walkability (Leis, 2014) and employment accessibility (Avner and Lall, 2016). We add to this body of work by exploring inequality in access to health across residential types and incomes and by comparing all three modes of transport.

Finally, a relevant study in Buenos Aires, used OpenTripPlannerAnalyst, a tool developed by Conveyal for the World Bank, to calculate employment accessibility by car and public transit (Quirós and Mehndiratta, 2015). This work compared the ratio of how much more you can reach by car than by transit for different neighborhoods and found that jobs are predominantly accessible by car; only in the center city does the transit system provide comparable levels of access. They also found that urban growth has been happening in places with little public transport access (particularly in gated communities).

By measuring and visualizing accessibility in Nairobi we contribute to the literature in the following ways. First, we add to what is currently known about the relationship between transport and land use in Nairobi by analyzing mobility and accessibility across the entire city for all the three primary modes of travel: walking, paratransit, and driving. The richness of data available makes it possible to measure and visualize accessibility generated by the paratransit system, which has rarely been studied. Although this kind of semi-formal transit system is common to cities in the Africa, Asia, and Latin America, Nairobi is one of the only places where the entire system has been mapped and put into a data format that can be used for measuring access (Klopp et al., 2015; Williams et al., 2015). A privately operated system could offer some benefits in terms of flexibility and demand responsiveness or it could focus and limit its service to only certain subsets of the population which are most profitable (Mutongi, 2006; Woolf and Joubert, 2013). A question remains about how this system, and paratransit systems in general, provide for
greater urban accessibility. Finally, unlike previous studies, we compare the provision of transportation and access to health facilities across residential types with a focus on understanding if access to health is equitably distributed across the city, across modes, and across income groups.

### 3.3 Study Context

From 800,000 residents in 1980, Nairobi grew to 3.1 million by 2009 and the city is expected to grow to 5.2 million by 2030 (Nairobi City County, 2014a). At the same time, the city has expanded outwards, maintaining fairly low density, especially in high income areas in the western part of the city. The majority of people rely on the minibus system to move around the city and it accounts for 40.7% of all trips (Nairobi City County, 2014b). This system consists of lower capacity minibuses, often 14-seaters called matatus, which are privately owned and operated by individuals or small business groups organized into cooperatives. Limited commuter rail also exists and is slated for expansion. However, a substantial portion of the population is unable to afford any kind of motorized transportation and so must live within walking distance of employment opportunities often in slum conditions (Salon and Aligula, 2012). For this reason, walking accounts for 39.7% of all trips. Private automobiles (including taxis) account for 13.5% of all trips, and two-wheelers account for 5.4% (Nairobi City County, 2014a). Car ownership rates have been on the rise with almost 30% of households owning a car by most recent estimates (ibid.).

In a survey of 1,751 slum households in Nairobi, Salon and Gulyani, (2010) find that, in contrast to other cities, poor residents often have physical access to public transit, but
that affordability remains a major issue. Only 38% of slum households have at least one member who regularly uses motorized transport compared to 80% of households citywide. In fact, matatus are the only form of motorized transport that slum residents reported using for any trip. The researchers highlight that slum residents in Nairobi do not have a mode 'choice'; they walk practically everywhere they go because they cannot afford other options. From a travel survey of 2,105 households throughout Nairobi, Salon and Aligula, (2012) link transport options to residential location. With low car ownership rates, they demonstrate that the middle income group is dependent on the matatu system. They also find that a large number of households must live within walking distance of work because they cannot afford any motorized transport options. This means that households may be choosing to live in slums in order to be closer to opportunities. The tradeoff between residential quality and location-based accessibility is one that we explore further in this paper.

Nairobi also has a poor-quality, fragmented road network, and traffic congestion is some of the worst in Africa and poised to get worse with the increase in motorization (Cervero, 2013). Recent transport planning has tended to focus on car users by emphasizing major highway expansion and improving the road network by building link roads and bypasses as well as some “smart city” work on traffic signals (Klopp, 2012; Nairobi City County, 2014a). Many of these projects plan for major highway development through densely populated, poor neighborhoods without careful attention to designing for the minibus system and non-motorized transport. This would very likely reinforce economic inequality and spatial segregation especially as highways often disrupt the primary mode in these neighborhoods which is walking (Hagans, 2013; Klopp, 2012; Manji, 2015).
recently, following a growing numbers of African cities, Nairobi is planning a Bus Rapid Transit (BRT) system and many highway expansions are now being justified based on their ability to contribute to the proposed BRT system. Further, Nairobi’s latest master-plan recognizes the need for modal shift to public and non-motorized transport but is silent on the access and social inclusion issues in the city (Nairobi City County, 2014c).

Overall, the absence of accessibility data, metrics and analysis within Nairobi’s transportation planning means that opportunities to improve connectivity and spatial equity are most likely being missed. In fact, some projects could be making accessibility for the majority worse. In the past, lack of data might have been a barrier but minibus and land-use data are now available to use for accessibility analysis (Williams et al., 2015; Williams, Marcello, and Klopp, 2014). Based on this data, an employment accessibility study has been conducted by the World Bank (Avner and Lall, 2016; The World Bank, 2016). They find that access to jobs is spatially unequal between cars and transit, with cars able to reach more formal economic opportunities within 30 minutes (The World Bank, 2016). Avner and Lall, (2016) explore if accessibility can be increased by modifying land use patterns. They find that better coordination between land use and transport can increase the share of overall job opportunities available within a given timeframe, although they also find a tradeoff where increasing the jobs-housing balance may actually decrease average accessibility (ibid.). Our study builds and expands on this important emerging work within the policy world and contributes to the conversation on what kinds of metrics might be developed to better guide transportation planning.

They find that in some instances increasing the jobs-housing balance may actually decrease average accessibility. We compare our findings to the research on access to jobs
The origin grid for all modes consist of points in 1.15°S to 1.40°S to 36.65°E to 37.17°E, at a resolution of 0.01°, or about 1 km. This span encompasses all of Nairobi county.

The size of the destination grids for each origin point is such that the furthest destinations are about two or more hours distant. For walking and paratransit, destinations
0.16° or about 18 km distant are sampled. For walking, this results in grids for which the shortest time to the furthest sampled point is 6.8 hours and the median furthest point time is 12.4 hours. For paratransit, the minimum time is 4.1 hours and median time is 7.9 hours. For driving, destinations 0.40° or about 44 km distant are sampled, and the minimum furthest time is 1.9 hours and median furthest time is 3.2 hours. These minimum hours ensure that we do not exclude any relevant destinations due to censored data. Destination grids have a higher resolution than origin grids, with grid points 0.004° or about 400 m apart. Figure 3.1 shows the average travel time to each point in an origin’s destination grid, across all origin points. Colors fade to white at a distance of 2 hours. Boxes denote the range of sampled destinations, relative to the origin location. The three maps are centered at an arbitrary example origin point in Nairobi, consistent across the three modes.

Figure 3.1: Average Origin-to-Destination Travel Time by Mode

Walking times are retrieved from the MapQuest transit route matrix interface. The MapQuest route matrix reports the estimated time to walk the fastest route between two points, avoiding limited access roads for pedestrian timing.¹ If the destination is unreachable,
able, MapQuest will sometimes report the time to the closest reachable point. If the dis-
tance reported for such a partial route is less than the straight-line distance from the
origin to the destination, the observation is dropped. Origin locations for which over 50% of
destinations are unreachable or dropped are retrieved using the Google Maps distance
matrix interface instead, as described for driving.

Driving times are collected using the Google Maps distance matrix interface. The
Google Maps distance matrix provides shortest driving distances using the road network
and walking distances using sidewalks and pedestrian paths.² MapQuest and Google
Maps routes are similar, with Google Maps able to provide complete routes from ori-
gins to destinations more often. Google Maps limits data collection more than MapQuest,
motivating our use of both services.

We query driving times with and without congestion. In the absence of congestion,
driving times are based only on the road class and assumed velocity for that class. Driving
duration with traffic is based on historical traffic conditions for a given day of the week and
time of day. We assume a departure time of 7:30 am (local time) on a Tuesday, representing
moderate weekday traffic.

Walking and driving times are first queried at 100 locations for each origin point, and
then extended as described below. The initial 100 points are arranged in a 10 x 10 grid,
extending 0.04° (4.4 km) from the origin for walking and 0.16° (18.9 km) for driving. The
entire collection of destination grids for each origin point is then used to determine times
to further locations and interpolated to higher resolution. The total time required to travel

from an origin point to a destination point in the final grid is the shortest time to leapfrog from one origin point to another, summing the origin-to-destination times in each step.

Paratransit connections are detailed in the form of a General Transit Feed Specification (GTFS) and made open and available by the Digital Matatus Project, a research consortium, who generated and disseminated the data (Williams et al., 2015). The GTFS data includes waiting, departure, and estimated transit times from each stop, and describes transfer points and transfer times between the routes. We find the minimum time to travel from an origin point to a destination point by estimating the walking time from the origin to each station, followed by all possible rides and connections, followed by the walking time from each final station to the destination. Walking times for paratransit are estimated using a straight-line path at an average speed of 4 km per hour. If this total is greater than the time to walk from the origin to the destination without using paratransit, then the walking time is reported instead. We only consider paratransit trips with boarding times between 7am and 9am on Mondays, but allow the trip to start at any time in this span that minimizes total travel time. The Digital Matatus data was largely collected onboard matatus, so it gives an estimate of actual travel times (inclusive of time spent at stages or delayed due to traffic congestion). Paratransit transit times are queried at the full resolution, rather than using a leapfrog approach.

Calculating Accessibility

To understand how service provision varies across modes, we use the following measure to approximate mobility at each grid point in Nairobi:
\[ M^v_i = \sum_{j \neq i} I(t^v_{ij} \leq t_{\max}) \]

where \( M^v_i \) is the mobility at origin location \( i \) for transportation mode \( v \), \( t^v_{ij} \) is the travel time in minutes between points \( i \) and \( j \) on mode \( v \), and \( I(\cdot) \) is an indicator function that is 1 if \( t^v_{ij} \) is less than or equal to \( t_{\max} \) of 60 minutes. This measure counts the number of other grid points that an individual can reach in 60 minutes from a given grid point. We use origin points \( i \) that fall within Nairobi City County but destination points \( j \) can be outside the city limits.

In addition to calculating mobility across modes, we want to understand access to specific activities. The following cumulative opportunities measure was used to approximate access to health facilities at each grid point in Nairobi. This measure is often used in accessibility analyses because it is easy to calculate and interpret. It is given by:

\[ A^v_i = \sum_{j \neq i} O_j \cdot I(t^v_{ij} \leq t_{\max}) \]

where \( A^v_i \) is the level of access at origin zone \( i \) for mode \( v \), \( O_j \) is the number of opportunities in destination zone \( j \), and \( I(\cdot) \) is an indicator function that is 1 if the time \( (t^v_{ij}) \) to get from origin zone \( i \) to destination zone \( j \) using mode \( v \) is less than or equal to \( t_{\max} \), which we set to 60 minutes. We use the travel times generated across a grid as explained previously. A variety of destination types can be used, and for this analysis we use data on medical facilities. The medical facilities included in the opportunities variable consist of hospitals (private or public), health centers, dispensaries, private clinics, nursing homes, and institutional health facilities (such as at schools, universities, prisons, etc.).
To calculate the number of opportunities, we associate each facility of interest, such as a hospital, with a point on the destination grid. Facilities are associated with the destination grid point closest to their centroid, excluding points beyond the range of the sampled destination points. Data on health facilities is for 2007 and comes from the Kenya Bureau of Labor Statistics³. Although 60 minutes is a somewhat arbitrary cutoff, we choose it because it is larger than the average travel time per trip in Nairobi of 47 minutes (The World Bank, 2016). Additionally, we only include medical facilities that fall within Nairobi.

Maps of the paratransit routes and the health facilities in Nairobi are shown in Figure 3.2. For the paratransit map, darker lines indicate more bus routes operating along that road. The paratransit network is dense close to the CBD. Routes primarily run from outlying areas into downtown. There are more health facilities around central Nairobi, although they are disbursed across the city. All calculations were performed in R using a number of packages⁴.

Figure 3.2: Distribution of Paratransit Routes and Health Facilities

³This data was downloaded from Kenya Open Data (http://www.opendata.go.ke/) on May 20, 2016.

Residential Typologies

Data on residential typologies comes from the UN Habitat Global Water Operators’ Partnerships Alliance’s (GWOPA) pilot project on Access to Water in Nairobi (Ledant et al., 2011). Using remote sensing data of a set of composite Quickbird images from October 2009 this work classified land cover into different land uses in Nairobi. Residential plots were further classified into 17 distinct categories of housing based on having particular combinations of physical characteristics. Physical characteristics included density of vegetation, plot size, attached or detached housing, single or multiple stories, gated space, and roof material. In March and April 2011, they conducted a survey of 817 households, sampling across the different residential categories. Based on the assumption that socioeconomic characteristics for non-sampled neighborhoods would be similar to sampled neighborhoods of the same type, they assigned mean values to each neighborhood type for all socioeconomic characteristics from the survey. For average income, they further grouped the neighborhood types into 7 aggregated income classes. In the survey, income ranges were recorded based on respondents’ estimation of household income. The median value was normalized by the number of household members and extrapolated to the neighborhood level. For the purpose of our study, we take these seven aggregated classes and order them from very low to very high income. These levels and a description of the residential typology is shown in Table 3.1 and mapped in Figure 3.3. More information on the physical characteristics that define each residential type and the income by neighborhood type can be found in the GWOPA’s Access to Water Technical Report (ibid.).

To explore how access varies by residential type and location we run the following
Table 3.1: Ordering of Residential Typologies

<table>
<thead>
<tr>
<th>Level</th>
<th>Income* (KES)</th>
<th>Description of Neighborhood Typology from Ledant et al., (2011)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very High</td>
<td>39,890</td>
<td>Detached housing on very large plots in intense vegetation (110)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Detached housing on large plots in lush surroundings (120)</td>
</tr>
<tr>
<td>High</td>
<td>22,084</td>
<td>Attached housing on medium plots in lush surroundings (130)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Moderate density apartment buildings (250)</td>
</tr>
<tr>
<td>Medium High</td>
<td>13,352</td>
<td>Attached housing on small sized plots with some vegetation (211)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Detached housing on large plots in lush surroundings (120)</td>
</tr>
<tr>
<td>Medium</td>
<td>6,153</td>
<td>Attached housing on small-sized plots with some vegetation (212)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Moderate-density apartment buildings (322)</td>
</tr>
<tr>
<td>Medium Low</td>
<td>3,854</td>
<td>Institutional housing (240)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Scattered detached housing (270)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Attached housing on small-sized plots with some vegetation (321)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>High-density lower-quality tenement buildings (330)</td>
</tr>
<tr>
<td>Low</td>
<td>2,165</td>
<td>Institutional housing (220)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Institutional housing (230)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Rural low-quality housing (260)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Lower-quality housing under development (311)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Planned lower-quality housing (313)</td>
</tr>
<tr>
<td>Very Low</td>
<td>1,301</td>
<td>Very low-quality housing (slums)</td>
</tr>
</tbody>
</table>

* Income is the median value of per capita income from each neighborhood type that makes up the aggregated class. Numbers in parentheses are the housing type codes from Ledant et al.

Figure 3.3: Map of Residential Typologies
regression:

\[ A_p^v = \alpha + \gamma \text{distCBD}_p + \sum_L \beta_L \text{ResiType}_p^L + \varepsilon_p \]

Where \( A_p^v \) is the level of access at residential plot \( p \) for mode \( v \), \( \text{distCBD}_p \) is the straight-line distance (in kilometers) from the centroid of residential plot \( p \) to the central business district given by the coordinates 1°16'59.99" S, 36°49'0.01" E, \( \text{ResiType}_p^L \) is a series of indicator variables set to 1 if residential plot \( p \) is of residential type \( L \), and \( \varepsilon_i \) is the residual error. Residential types \( L \) include “very low”, “low”, “medium low”, “medium high”, “high”, and “very high”, as defined in Table 3.1. “Medium” is the reference level.

### 3.5 Results

The results show how accessibility varies spatially across Nairobi and across residential typologies. In particular we find higher levels of access to health near the Central Business District (CBD) for all three modes. We also find significant variation in accessibility across residential typologies with the highest types tending to have the lowest access for a given mode and lower residential types having comparatively better walking accessibility. Controlling for distance from the CBD, two residential types stand out. The highest type, primarily large homes in gated communities, have very low access for all three modes, while the “medium low” type, characterized in part by tenement apartment buildings, has significantly better access than other residential types.
Accessibility by Mode

The maps in Figure 3.4 show access to health by mode across Nairobi. We see that driving provides very high levels of accessibility. The scale is logarithmic so this is magnitudes larger than walking accessibility levels. In the map of access to health by paratransit we see the shape of the matatu bus network, and higher levels of access along transit routes. Central city locations have a comparative advantage for all modes, but particularly for someone who walks because walking access is very low outside of this area. Figure 3.8 in the Appendix shows transport provision by mode, using the mobility measure, with similar general trends.

Table 3.2: Summary Statistics of Mobility and Accessibility Measures

<table>
<thead>
<tr>
<th>Mode</th>
<th>Mobility ($M_i^v$)</th>
<th>Accessibility ($A_i^v$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>St. Dev.</td>
</tr>
<tr>
<td>Walking</td>
<td>10.3</td>
<td>5.6</td>
</tr>
<tr>
<td>Paratransit</td>
<td>79.0</td>
<td>60.0</td>
</tr>
<tr>
<td>Driving</td>
<td>513.3</td>
<td>189.1</td>
</tr>
<tr>
<td>Driving (no traffic)</td>
<td>751.3</td>
<td>155.2</td>
</tr>
</tbody>
</table>

Note: Sample includes 566 origin points in Nairobi. The units for the mobility measure are number of grid points. The units for the accessibility measure are number of medical facilities.

Figure 3.5 and the accompanying Table 3.2 show how the mobility and accessibility metrics compare across modes. The mobility measure, $M_i^v$, captures the number of grid points $j$ that are reachable within 60 minutes of travel from each origin point $i$ using a given mode. The accessibility measure, $A_i^v$, captures the number of health facilities that are reachable within 60 minutes. Figure 3.5 shows the empirical cumulative distribution function of the data computed for each metric. The x-axis is the value of the mobility or accessibility measure and the y-axis is the proportion of the observations in the data that have that level of mobility (or accessibility) or less. For example, in Figure 3.5b, for walking
Figure 3.4: Access to Health

(a) Walking

(b) Paratransit

(c) Driving
we see that 75% of locations have access to 2 health facilities or fewer, or alternatively that 25% of locations have access to more than 2 health facilities.

The mobility measure describes characteristics of the transport system. Walking mobility ranges from 0 to 29 with a mean of 10.3; paratranist mobility ranges from 0 to 340 with a mean of 79.0; and driving mobility is much larger with a range from 0 to 810 and a mean of 513.3. We see that driving has a significant advantage over walking and paratransit in reaching more points throughout the city. On average one can reach 2% (10.3/513.3) of the locations (grid point centroids) on foot as by car and 15% (79.0/513.3) by matatu as by car in one hour. Furthermore, traffic congestion has a large impact. Using our estimates, it reduces the average number of locations reachable in 60 minutes by a third (from 751.3 to 513.3).

In Figure 3.5b, we see that the car again provides the highest level of access when measured as access to health facilities, but that the interaction between transport and land use is important to consider for paratransit. In particular, when we take into account where health facilities are, we see that, because paratransit serves the areas where there
are more health facilities, the comparative advantage of driving compared to paratransit is reduced. On average one can reach 29% (33.0/115.5) of health facilities by matatu as by car in one hour, which taking accessibility of health care opportunities into account is twice as high a comparison based on mobility alone.

Accessibility by Residential Typology

Figure 3.6 shows the mean and standard error of access to health facilities by residential type for each mode. In general, lower residential types have higher levels of access to health by walking. The “low” residential type is the main exception with very low levels of access to health compared to the other lower residential types. It is also the furthest from the central business district (CBD) on average at 11.0km versus 6.7km for “very low” and 10.0km for “medium low” types. This result is being driven in part by the residential plots on the western side of the city, in the neighborhoods of Kawangware, Kangemi, and Riruta. They make up a large proportion of the observations for the “low” category. Trends are less obvious for driving or paratransit, except that the “very high” and the “low” residential types have much lower access than other types.

Figure 3.6: Access to Health by Residential Level
Figure 3.7: Access to Health Facilities by Distance for Residential Types

Figure 3.7 shows the relationship between access to health and distance to the CBD by residential typology for each mode. The graph includes a scatterplot of the data and a linear regression line. The slope of the regression line represents the change in the number of health facilities reachable in 60 minutes for a 1km change in the distance to the CBD. The negative slope demonstrates that locations further from the CBD tend to have lower levels of access to health. It also shows the huge comparative advantage afforded by paratransit travel. Switching from walking to paratransit provides 10 times as much as access to health, while switching from paratransit to driving provides 1.4 times more. The regression results shown in Table 3.3 confirm what we see in Figure 3.7. The average slope is steepest for paratransit (-8.058), followed by driving (-3.968), and walking (-1.148), and each is statistically significant. It is not surprising that access decreases more quickly going away from the CBD for paratransit than for the other modes since the transit system is characterized by fixed routes that converge on and are very dense.
Table 3.3: Regression of Accessibility on Residential Type

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Walking Access</th>
<th>Paratransit Access</th>
<th>Driving Access</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Distance to CBD</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>2.200***</td>
<td>-0.207</td>
<td>-0.716</td>
</tr>
<tr>
<td></td>
<td>(0.640)</td>
<td>(2.667)</td>
<td>(2.335)</td>
</tr>
<tr>
<td>Very Low</td>
<td>2.993***</td>
<td>-8.166***</td>
<td>0.406</td>
</tr>
<tr>
<td></td>
<td>(0.517)</td>
<td>(2.153)</td>
<td>(1.885)</td>
</tr>
<tr>
<td>Medium Low</td>
<td>4.999***</td>
<td>13.802***</td>
<td>8.259***</td>
</tr>
<tr>
<td></td>
<td>(0.555)</td>
<td>(2.312)</td>
<td>(2.024)</td>
</tr>
<tr>
<td>Medium High</td>
<td>-1.357*</td>
<td>-5.073*</td>
<td>2.566</td>
</tr>
<tr>
<td></td>
<td>(0.502)</td>
<td>(2.091)</td>
<td>(2.037)</td>
</tr>
<tr>
<td>High</td>
<td>-1.878***</td>
<td>-8.070***</td>
<td>-5.718**</td>
</tr>
<tr>
<td></td>
<td>(0.502)</td>
<td>(2.091)</td>
<td>(1.830)</td>
</tr>
<tr>
<td>Very High</td>
<td>-0.639</td>
<td>-17.369***</td>
<td>-20.81***</td>
</tr>
<tr>
<td></td>
<td>(0.517)</td>
<td>(2.154)</td>
<td>(1.885)</td>
</tr>
<tr>
<td>Constant</td>
<td>13.309***</td>
<td>130.435***</td>
<td>184.494***</td>
</tr>
<tr>
<td></td>
<td>(0.469)</td>
<td>(1.955)</td>
<td>(1.712)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,598</td>
<td>1,598</td>
<td>1,598</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.446</td>
<td>0.751</td>
<td>0.503</td>
</tr>
<tr>
<td>Residual Std. Error (df = 1590)</td>
<td>4.630</td>
<td>19.286</td>
<td>16.884</td>
</tr>
<tr>
<td>F Statistic (df = 7; 1590)</td>
<td>184.920***</td>
<td>688.476***</td>
<td>232.310***</td>
</tr>
</tbody>
</table>

Note: *p<0.05; **p<0.01; ***p<0.001

in the CBD. Furthermore, the ability to transfer between routes is easier near the CBD, which is another factor increasing accessibility.

The regression results in Table 3.3 also demonstrate that, controlling for the distance from the CBD, higher residential types tend to have lower levels of access than other residential types. Higher residential types (“medium high”, “high”, and “very high”) reach up to 1.878 fewer health facilities in an hour by walking, between 5.073 and 17.369 fewer by paratransit, up to 20.082 fewer by driving than the “medium” residential type (which is
the reference category in the regression), although the “very high” residential type is not statistically significant for walking access and the “medium high” type is not significant for driving access. On the other hand, lower residential types (“very low”, “low”, and “medium low”) are able to reach between 2.200 and 4.999 additional health facilities in an hour by walking than the “medium” residential type given the same distance from the CBD. Overall patterns for lower residential types is less clear for paratransit and driving.

Of particular note are the exceptionally high levels of access to health facilities for the “medium low” residential type and the exceptionally low levels of access for the “very high” residential type. Controlling for distance from the CBD, the “medium low” residential type has the highest average levels of access compared to other residential types for all three modes. This residential typology includes large-scale multi-story tenement buildings such as in Huruma, Pipeline, Umoja, Inner Core, and Eastleigh; institutional housing such as in the neighborhoods of Bahati, Pangani, and Eastleigh including the old Indian quarters and housing developed during colonial rule to house African railway laborers; and the eastern part of Nairobi where private developers have built low-density single family homes. The tenement buildings are notable because of their very high population densities and poor conditions. A sample in Huruma estimates densities of approximately 5,242 people per hectare, which is extreme, even compared with late nineteenth century New York City tenements that reached 1,294 people per hectare (Huchzermeyer, 2007).

The other housing category that stands out is the “very high” residential type because it has exceptionally low levels of access to health facilities. This type is representative of detached housing on very large (often gated) plots of land. It is likely that this dispersed and land-intensive development leads to low levels of physical access. It is also a result of
the few health facilities located in these exclusive areas with restrictive zoning. Of course, we do not take into account the quality of these different facilities and the fact that lower income citizens may have better physical, or “nominal”, access but less ability to pay for services or “effective access”.

Discussion

Our findings highlight the interaction between transport and land use in shaping people’s ability to access urban amenities. Similar to work looking at access to jobs, we map and visualize accessibility across Nairobi by mode. Taken together, our work and the work by Avner and Lall, (2016), demonstrate what accessibility looks like across Nairobi including how different modes have different equity implications and what role urban form plays in shaping access. Both projects are made possible by having data on informal transit systems, which is clearly important for fully understanding the transportation network. Our findings are also in line with travel survey research in Nairobi. As Salon and Gulyani, (2010) find, a central city location may be particularly advantageous to people who walk because walking access is very low outside this area. For the large number of low-income households who cannot afford any motorized transport, living in slums near the CBD may be the only feasible option within walking distance of jobs or other amenities. This is an interesting parallel to studies in the U.S. that also find that low-income groups living in the inner city have better access to jobs (Grengs, 2012; Hess, 2005; Scott and Horner, 2008).

We add to this body of research by making explicit the relationship between housing
quality and transportation’s contribution to access to health facilities. In addition to finding that lower residential types have better walking access, we find notable results for the “medium low” and “very high” types, as compared to the “medium” residential type. The “very high” residential type stands out for having much lower driving and paratransit access, even after we control for the distance from the CBD. This is a somewhat counter-intuitive result that the highest quality housing has access to the fewest number of health facilities within 60 minutes. This type is representative of detached single-family housing on very large (often gated) plots of land. It may be that this dispersed and land-intensive development, leads to lower access. It could also represent a preference not for access, but for seclusion, a point made by Couclelis and Getis, (2000). In addition to being built for cars, some of these neighborhoods ban matatus from entering. Households in these neighborhoods often employ domestic workers, whose ability to get there is severely limited. This type of urban development appears to contribute to spatial segregation.

Our findings also highlight the issue of tenement housing, a rapidly growing residential form in Nairobi. The “medium low” residential type has significantly higher levels of access to health facilities and is characterized by both colonial-era institutional housing and by privatized high-rise apartment buildings. Huchzermeyer, (2007) draws attention to the growth in large-scale privately owned apartment buildings, likening them to modern-day tenements with extremely high population densities, insufficient planning and regulation, and driven by profit-maximization. However, we find that the location of this residential type near transport networks has a significant advantage in accessibility which may explain their attraction.

The accessibility measures used here are estimates and do not capture all the factors
that influence individual travel decisions. For example, these location-based measures do not take into account the variation across individuals such as how access differs by age, gender, or physical ability, and do not take into account financial constraints, such as ability to pay for paratransit, or a car. The results can be used to understand how the potential for access compares across neighborhoods, and if used in practice should be compared with actual travel behavior. We recommend further study on the complex factors that effect travel behavior (Curl, Nelson, and Anable, 2011). One area for future research is to build on this work by incorporating travel survey data into these measures and analysis in a way that reflects the different constraints that individuals face. Since accessibility is a function not only of location, but also of personal characteristics, updated measures could provide additional information about social exclusion (Páez et al., 2010; Preston and Rajé, 2007).

Another limitation was the availability of high-quality land use data and residential data. As a proof of concept, we focused on health care facilities, but future work should be done to understand how the distribution of health care facilities compares to other destination types and if health care facilities are an appropriate proxy for access to opportunities more broadly. Health facility data tends to be more readily available than local land use data, so could be an important component for future accessibility studies in the low-income country context. Additionally, we do not take into account the variation in quality of health care facilities, which future research should explore. Furthermore, the residential typology data is an estimate. In creating the residential typology data, field surveys were conducted and income was extrapolated to all neighborhoods within the same category. The accuracy of the extrapolation has not been verified and has an un-
known influence on our results (Ledant et al., 2011). Furthermore, Nairobi tends to have a mix of people with different income levels living in close proximity; a shortcoming of the data is that the aggregated categories do not capture the variation in housing and income level represented in a single neighborhood.

An important point for policy is that these findings show a static picture of how accessibility and residential quality are related, but in reality there is a dynamic tradeoff between the two. Increasing accessibility could increase residential rents, in turn affecting which income groups live in different neighborhoods. Because this is a complex relationship and little is known about gentrification in the African cities, policies aimed at increasing equity should address transportation and housing together, as a comprehensive social policy package.

Finally, there are a number of other factors that impact transportation service that were not included. For example, future research could look at how access varies over a 24-hour period and how reliability and safety vary across modes. These may be important when considering paratransit access and important features for understanding how equitable access is across groups (El-Geneidy et al., 2016a; Fransen et al., 2015; Klopp and Mitullah, 2015). Another very important factor that we did not take into account is the quality of walking infrastructure. The Nairobi Master Plan highlights how sidewalks are narrow and in many places do not exist at all, particularly not as a formulated pedestrian network and that there is not sufficient pedestrian signage or crossing signals. These street-level characteristics may have a huge impact on access that we do not currently capture and needs to be explored. Although we use estimated travel times with congestion at one point in time, this is only an approximation and the impact of congestion on
accessibility deserves further study.

3.6 Conclusion

Our findings make explicit the relationship between housing quality and transportation access to health. The results show how accessibility varies spatially across Nairobi, across modes, and across residential typologies. In particular we find higher levels of access to health near the Central Business District (CBD) for all three modes: walking, semi-formal transit (or paratransit), and driving. The central location may be particularly advantageous to people who walk because walking access is very low outside this area. We also find significant variation in accessibility across residential typologies with lower types having higher levels of access by walking than higher quality residential types. The highest residential type has the lowest access to health for paratransit and walking which may raise problems for the many low income people living and working in these areas. We also find that the “medium low” residential typology, which includes tenement type apartments, offers significantly better access to health facilities than other residential types after controlling for distance from the CBD.

Focusing on accessibility, or the interaction between transportation and land use, is important for understanding how well transportation systems serve the needs of urban populations. We found that although driving provides much higher levels of mobility than paratransit, when we incorporate land use information, the advantage of driving over paratransit is smaller. Evaluating transportation projects based solely on physical characteristics of the transport system such as travel time savings, could underestimate
the importance of paratransit or other systems that work in conjunction with land use. Using accessibility measures to understand the relationship between transport and land use could also be important in light of the new Sustainable Development Goals, including the one focused on transit that aims to ‘By 2030, provide access to safe, affordable, accessible and sustainable transport systems for all, improving road safety, notably by expanding public transport, with special attention to the needs of those in vulnerable situations, women, children, persons with disabilities and older persons’ (United Nations General Assembly, 2015). Accessibility measures may be an appropriate way to make this goal measurable and context relevant.

Furthermore, we find strong evidence for the ways that housing is linked to transport, particularly in how households may be making a tradeoff between living conditions and transportation accessibility. We see this happening for walking access across all levels of residential quality. People may live in lower quality housing precisely because it gives them walking access when no other modes are affordable. Furthermore, middle-income households may be compromising on private tenement-like apartments because it gives better access to the modes they can afford and to urban opportunities. And finally, that at the highest end of the spectrum, residential developments for the wealthy may be built in a way that limits access to their neighborhoods. These findings put together, tell us that transport, land use, and housing will effect how successful policies are at improving travel throughout Nairobi County. To support equity and social inclusion, a social policy package that takes into account this complex tradeoff between housing and accessibility may be most appropriate.

The recent Master Plan for Nairobi recommends public transport development policies
including supporting a modal shift to public transport (with examining ways to improve the existing matatu and bus service), strengthening the existing rail service, and promoting Transit Oriented Development. The master plan also acknowledges that a developed non-motorized transport network is a prerequisite. In practice, transportation planning in Nairobi continues to focus on the implementation of road development plans with a focus on the mobility of wealthier car users (Klopp, 2012). Our work confirms the importance of improving the pedestrian environment and supporting public transport, particularly in making it affordable and linked with land use development. Careful interventions might focus on improving the way the modes used by the majority interact with land use and explore the use of subsidies and social support in order to increase access for all to important urban amenities and opportunities. We also recommend mixed use development and support for affordable Transit Oriented Development that may be already happening through Nairobi’s tenement-like buildings near matatu stops. Finally, in line with new global thinking, we need to move from theory to practice by mainstreaming accessibility and social inclusion as goals of urban development and planning. The push for data, metrics and more accessibility studies in cities like Nairobi might just help to achieve this important goal.
Appendix

Mobility Maps

The mobility maps in Figure 3.8 show the transport provision by mode across Nairobi. Specifically, the maps show the value of $M_i^j$, which is the total number of grid points $j$ that are reachable within 60 minutes of travel from each origin point $i$ using a given mode. We see that driving provides very high levels of mobility. Again, the scale is logarithmic. The provision of mobility by the transit system is more comparable to walking than to driving.

![Mobility Maps](image)

Figure 3.8: Mobility

(a) Walking  (b) Transit  (c) Driving


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