Environmental Determinants of Bicycling to Rail Stations in Chicago

by

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Abstract

Transit agencies are increasingly incorporating cycling into their programs through bicycle to transit initiatives such as indoor bicycle parking at rail stations as well as bicycles on buses and trains. In spite of the popularity and success of these programs, little research exists on the influences on the behavior, and transit planners and decision makers do not have a reliable way of gauging demand for bicycle facilities. This paper provides a brief overview of the literature on bicycling to transit, as well as cycling and transit behavior separately. We used annual counts of bicycles parked at Chicago Transit Authority rail stations and neighborhood GIS data to estimate longitudinal models of the environmental determinants of bicycling to rail stations. Results indicate that increased use of bicycle parking at rail stations is associated with higher station boardings, more bicycle parking facilities, lower residential density and crime, and fewer bus options, even while controlling for neighborhood demographics. Based on the findings, we recommend that practitioners use an assortment of policies and infrastructure improvements to expand the reach of the transit and cycling networks. In addition, planning professionals should take initiative to collect useful data to prove the success of cycling to transit programs.

Keywords: Bicycling, Public Transportation, Built Environment
Introduction

Transportation professionals are increasingly looking for nontraditional options to help complete transit and non-motorized networks, and many have turned to the complementary aspects of cycling and transit. A number of agencies in the United States and abroad have adopted policies in the last 15 years aimed at increasing the use of the two modes (Schneider, 2005), such as indoor bicycle parking at rail stations and allowing bicycles on buses and trains. The public benefits of these programs are numerous, as both bicycling and transit can improve health, increase access to jobs and services, promote equity for underserved populations, and reduce environmental impacts.

Studies have suggested that walking to transit stations can help meet daily physical activity benchmarks, and bicycling to transit may serve a similar health function (Berrigan, Troiano, McNeel, Disogra, & Ballard-Barbash, 2006; Besser & Dannenberg, 2005; Hoehner et al., 2005; Winters, Friesen, Koehoorn, & Teschke, 2007). The American College of Sports Medicine and the American Heart Association guidelines recommend that adults engage in at least 30 minutes of moderate physical activity at least five days a week, which can be achieved through bouts of 10 minutes or more that noticeably increase the heart rate (Haskell et al., 2007). Meeting these recommendations may help lead to lower rates of cardiovascular disease, hypertension, type 2 diabetes mellitus, obesity, colon cancer, breast cancer, anxiety and depression (Haskell et al., 2007; Kesaniemi et al., 2001).

Bicycling to transit also expands the reach of the transit and bicycling network, which may help reduce dependence on automobiles. People whose origins and destinations are more than one-quarter mile from transit stations are less likely to walk to transit than those whose origins and destinations are within one-quarter mile (R. Cervero, 1998; Dill, 2003). Similarly, studies have shown that distance to a destination is negatively correlated with bicycling (Jackson & Ruehr, 1998; Pucher & Buehler, 2006; Stinson & Bhat, 2004). Integrating cycling and transit may address both of these barriers by allowing people to travel farther to stations while still being able to ride on a train or bus for the majority of the distance to work (Schneider, 2005). Transit can also carry cyclists through areas that are less conducive to cycling. As an added benefit, cycling solutions for connecting people to transit may be significantly more cost effective than expanding the transit network itself (Cottrell, 2007).

Enhancement of bicycle and transit amenities may particularly benefit low income and underserved populations, who are more likely to use alternative modes of travel. (Plaut, 2005; Pucher & Renne, 2003). Additionally, Meletiou and colleagues (2005) found that investment in bicycle infrastructure may lead to economic growth in an area. Integrating cycling with transit could result in similar development in economically deprived communities.

Bicycling does not contribute to noise or air pollution, and damages the environment less than driving an automobile (McCarthy, 1999). Similarly, riding transit instead of taking a car can limit congestion and improve air quality (Ogilvie, Egan, Hamilton, & Petticrew, 2004). Integrating bicycling with transit, thereby increasing the share of the two modes combined, may lower environmental impacts if chosen over driving alone.
Bicycle to transit programs have been largely successful, and research has documented significant use of bicycle facilities provided by transit agencies (Federal Transit Administration, 1999; Martens, 2007; Schneider, 2005). King County Transit estimated more than 40,000 bicycle-carrying passengers in 1999 while Caltrain reported that more than 2,000 cyclists a day brought their bicycles on board the passenger rail line between San Francisco and Silicon Valley during the same year (Federal Transit Administration, 1999). San Diego Metropolitan Transit System estimates nearly 600,000 bicycle trips served annually through its facilities (Schneider, 2005). Despite the emerging appeal of the programs, bicycle to transit behavior has been overlooked in research, and little has been written on travelers who use the facilities and their environments (Schneider, 2005).

Case Study: Chicago Transit Authority’s Bike and Ride Program
In 1999, the Chicago Transit Authority (CTA) initiated a program to encourage people to combine bicycling and transit. The program, called Bike and Ride, has three major components: allowing bicycles on “L” trains except during rush hours, equipping all 2,000+ buses with racks that carry up to two bicycles, and providing indoor bicycle parking at more than 75 rail stations on the system. Bike and Ride is part of a larger mission by the Mayor Richard M. Daley and the Chicago Department of Transportation to “make Chicago the most bicycle friendly city in the United States” (Mayor's Bicycle Advisory Council, 2006).

Anecdotal evaluation of the program by CTA is encouraging. Interviews with Bike and Ride users indicate that they are very satisfied with the services offered. In addition, in 2006, CTA employees surveyed users of the indoor parking facilities to ascertain demographic information and transit behavior (Figure 1). Results indicated that most people who parked their bicycles at rail stations also used another Bike and Ride program component (e.g., bike on bus or bike on train) and rode CTA trains at least four days per week, indicating that the use of Bike and Ride may be related to overall use in transit ridership.

This paper assesses one component of the Bike and Ride program. We used annual counts of bicycles parked at the indoor facilities, combined with geospatial land use, demographic, and policy data, to elucidate possible influences on the use of bicycle to transit programs. Understanding environmental characteristics related to Bike and Ride participation can help policy-makers better leverage resources to maximize the use of facilities and can help researchers better understand the role of the built environment in transportation decisions.

Literature and Theory: An Environmental Approach
The literature shows little exploration of the environmental influences on Bike and Ride participation (Krizek & Johnson, 2006; Schneider, 2005). Limitations of research design may partially account for this absence, as it can be difficult to use data to demonstrate the sometimes intangible differences in environments that affect cycling behavior. Krizek and Johnson (2006) noted that most studies have used data from only one or two neighborhoods to research the value of cycling facilities. Examining travel behavior in a number of different neighborhoods might reveal more nuanced environmental influences on people’s decisions to bicycle to transit.

Instead of focusing on environmental factors, both transportation and health literature often cite individual choice as a key decisional factor in travel behavior. When characteristics of the built
environment are included in analyses, their influence is often nullified by the role of travelers’
preferences (Barnes & Krizek, 2005; Handy, Cao, & Mokhtarian, 2005; Moudon et al., 2005).
However, Zhang (2004) found that mixing of land uses, density, and design predicted variation
in mode choice. Furthermore, bicycling and public transit use have each been independently
associated with environmental characteristics (R. Cervero & Radisch, 1996; R. Cervero &
Landis, 1997; Dill, 2003; Ewing & Cervero, 2001; Kuby, Barranda, & Upchurch, 2004; Pucher
& Renne, 2003; Schneider, 2005), indicating a potential influence of such characteristics in the
decision to Bike and Ride.

Environmental Determinants of Bicycling
A number of studies in the transportation and health fields have examined factors affecting de-
cisions to use non-motorized transport (Ogilvie et al., 2004; Pikora, Corti, Bull, Jamrozik, &
Donovan, 2003; Saelens, Sallis, & Frank, 2003; Sallis, Frank, Saelens, & Kraft, 2004; G. C.
Wendel-Vos et al., 2004). The built environment can be important in changing travel behavior,
as people will substitute active travel modes in more supportive home and worksite neighbor-
hoods (Dill & Wardell, 2007; Rodríguez, Khattak, & Evenson, Winter 2006). While these types
of findings have received much attention, in a majority of them, cycling is grouped with walk-
ing behavior. Krizek and Johnson (2006) note that the needs for cycling can be different than
those for walking (e.g., bike lanes versus sidewalks) and that the modes can serve very different
purposes. For these reasons, they recommend separate research.
Some evidence does indicate that the built environment can influence people’s decision to bicycle (Hoehner et al., 2005), and cycling amenities have been shown to influence travelers’ decisions when other barriers such as weather would otherwise prevent them from cycling (Brandenburg, Matzarakis, & Arnberger, 2007; Pucher & Buehler, 2006; Winters, Friesen, Koehoorn, & Teschke, 2006). Other researchers find that relationship to be only moderate (Moudon et al., 2005). Bicycle lanes and off-street trails, both characteristics of the built environment, may positively influence the decision to bicycle (Garrard, Rose, & Lo, 2008; Hoehner et al., 2005; Tilahun, Levinson, & Krizek, 2007). Some studies indicate that people living close to bicycle facilities were more likely to make a bicycle trip, but this relationship was insignificant once the distance to the facility became lengthy (Krizek & Johnson, 2006; Moudon et al., 2005). Dill and Carr (2003) found that cities with more bicycle lanes per square mile were associated with higher percentages of bicycle commuters. Whether the presence of lanes actually generates more cyclists, however, is unclear (Barnes & Krizek, 2005; Dill & Wardell, 2007). Bicycle lanes are built in areas with high cycling demand more often than in areas of low demand. Barnes and Krizek (2005) argue that a longitudinal study, examining cycling demand over time, is the only approach for resolving this issue.

Correlating other environmental supports with cycling yields mixed results. Higher residential density and cycling appear to be related (Baltes, 1996; Winters et al., 2007), but the studies showing this relationship calculated densities using entire metropolitan areas, rather than specific neighborhoods. Nevertheless, high densities of goods and services near households can serve a great benefit for those who are walking and bicycling dependent (Ritsema van Eck, J., Burghouwt, & Dijst, 2005). Cervero and Duncan (2003) found diversity of land use at the origin (not the destination) to be the only significant built environment factor impacting walking and bicycling.

Most studies use surveys to determine the use of cycling facilities. Often, cycling behavior is measured by asking participants how often they use off street trails (Nelson & Allen, 1997; Ogilvie, 2004; W. Wendel-Vos, Droomers, Kremers, Brug, & van Lenthe, 2007). However, the use of trails may not be relevant for bicycling to transit, since people usually ride on local streets to arrive at transit stations in the middle of urban areas. Thus, the presence and use of on street facilities (i.e. bike lanes) may be a more appropriate measure of this behavior. In addition, objective outcome data, like observations of environmental characteristics or behavior, may be more useful than self-report since stated preferences and behaviors might not reflect actual neighborhood characteristics or travel choices (Moudon et al., 2005).

In spite of the limitations of grouping cycling and walking together (Krizek & Johnson, 2006), the similarities between the modes of travel may lend insight to additional environmental influences on cycling. Street connectivity has been identified as a contributor to walkability in neighborhood design (Leslie et al., 2005; B. E. Saelens, Sallis, Black, & Chen, 2003). Findings indicate that more street miles in suburban areas are associated with physically active transport in general (B. E. Saelens et al., 2003). However, using this measure for cycling may not be as effective, where less street crossings may be more desirable (Barnes & Krizek, 2005). By disaggregating bicycling from walking in such studies, researchers could get a better sense of how street connectivity affects bicycling specifically.
Transportation research and practice use the concept of “attraction” when explaining travel behavior (McNally, 2000); like a magnet, the more attraction a place has, the more likely a traveler is to go there, regardless of mode. For example, a potential destination could have a higher attraction if it contains a popular business or a large office which would make people more likely to choose that destination. Although we found no studies using attraction when looking at cycling to transit behavior, the basic correlation between attraction and destination choice indicates that certain characteristics of the transit station could influence the behavior. For example, transit ridership at a station, like number of customers in a store, could be an indication of its attraction, and thus could be related to cyclists’ choice to travel there.

In addition to the built environment, studies indicate that socioeconomic status, race/ethnicity, and gender could all influence bicycling (Garrard et al., 2008; Pucher & Renne, 2003; Winters et al., 2007). For example, those who are more educated may be more likely to commute on their bicycles (Barnes & Krizek, 2005; Plaut, 2005; Winters et al., 2007), and those who have higher incomes may be less likely to do so (Plaut, 2005). What is less clear is whether neighborhood demographics influence rates of bicycle to transit behavior. Although we found no studies that examined these neighborhood level relationships, correlations between individual characteristics and behavior suggest investigating neighborhood demographics as well.

Environmental Determinants of Riding Transit

In addition to cycling, the built environment may influence people’s decisions to ride transit. Neighborhood design factors, such as mix of land uses and presence of sidewalks, are strongly associated with transportation mode choice, particularly for commuting (Schwanen & Mokhtarian, 2005; Zhang, 2004). The proximity of transit stations is strongly associated with transit ridership (R. Cervero & Radisch, 1996; R. Cervero & Landis, 1997; Dill, 2003; Kuby et al., 2004; Schneider, 2005); those who live close to transit stations are more likely to use transit. Proximity of transit stations, in turn, is related to residential and commercial density, as more dense neighborhoods are more likely to have people living and working close to transit stations (Ewing & Cervero, 2001).

In cities with a higher population density or a higher concentration of jobs in the central business district, a smaller percentage of people travel by private automobile; those that do tend to travel shorter distances (van de Coevering, P. & Schwanen, 2006; Zhang, 2004). This indicates that both employment and population density may play a role in reducing the proportion of private auto use. Transportation researchers have tried to determine the directionality of this link, with some arguing that the presence of transit increases density in the built environment (R. Cervero & Landis, 1997) and others suggesting that higher residential density may foster higher ridership (Boarnet & Sarmiento, 1998). These two arguments are not mutually exclusive. The relationship between density and transit may be symbiotic, with each enhancing the other.

Another built environment factor affecting the use of rail transit is the comprehensive transit network itself. Higher quality bus service is associated with increased ridership (Ceder, 2001). In these areas, busses may preempt bicycles as the means of transport to a transit station. Conversely, if the time required to take the bus to the train far exceeds that of riding a bicycle, people may opt to bicycle to the station. Some bicycle commuters choose to bicycle because they
do not believe transit will get them where they want on time (Zacharias, 2002). For those individuals to opt to bicycle to transit, they must have a greater trust in the punctuality of the train system than they have in the bus.

The cost of transit has also been shown to be related to people’s transportation mode choice (Goodwin, 1992; Oum, 1991; Mayworm, Lago, and McEnroe, 1980). As fares increase, travelers are less likely to take transit. However, if fare changes reflect overall inflation, costs associated with driving a car (gas, insurance, etc.) may also rise. In this case, transit behavior may be less sensitive to fare increases.

Security and crime in and around transit stations are significant influences on both bicycling and riding transit (Kim, Ulfarsson, & Hennessy, 2007; Loukaitou-Sideris, Liggett, & Iseki, 2002). Crime might deter people from riding a bicycle to the station, leaving a bicycle at the station for the day, and riding transit. Indoor bicycle parking facilities may partially address theft concerns, but not other types of crime which can occur while riding a bicycle or train. The 2001 National Household Travel Survey (NHTS) (Pucher & Renne, 2003) indicates that socioeconomic status and race are strong indicators of transit ridership. Lower income, African American, and Hispanic households appear more likely to use transit. As with cycling research, NHTS compared individual characteristics with riding behavior. Demographic measures of neighborhoods may be important environmental influences on rates of transit use, and deserve further examination.

**Summary**

Bicycling to transit is a unique mode of transportation that promotes physical activity and enhances the environment. Understanding decisions to **Bike and Ride** requires a study of the influences on peoples’ travel decisions for both bicycling and riding transit, independently and together. Various demographic and neighborhood characteristics have been associated with decisions to cycle or ride transit, but literature on this combined mode of transportation, and how broader environmental determinants influence it, is limited.

Geographic information systems (GIS) data maps and bicycle parking count data from the Chicago Transit Authority can better reveal the nuanced relationships of these varying characteristics with bicycling to transit over time and help transit agencies better predict the number of bicycle parking facilities necessary when constructing stations. Furthermore, analysis of these data could help policy makers understand how to enhance environments to facilitate cycling to transit.

**Methods**

**Study Area**

There are 143 rail stations in the CTA system (Figure 2). Twenty stations are located outside the City of Chicago. To determine the neighborhood study area served by each station, we created station buffers designed to include the residences of most potential **Bike and Ride** consumers. In order to determine the size of the buffer, we used the results of CTA surveys left on bicycles parked at the stations in 2006. Surveyors delivered 203 surveys to 40 different stations and participants returned 92 surveys from 24 different stations, equaling a 45% participant response
Figure 2: CTA System Map
rate and a 60% station response rate. One of the survey items asked “How far did you bicycle to get to this station?” More than 50% of respondents indicated they rode between ½ mile and 1 mile to arrive at the station, more than twice the percentage of the next most common response (1-2 miles). Less than 10% of respondents reported bicycling less than ½ mile to the stations. Given this information, we used ESRI ArcMap® GIS 9.2 to create a one mile buffer around each station to serve as neighborhood areas for analysis (Figure 3).

Data Sources
We acquired data from a variety of sources, including: Chicago Transit Authority (www.transitchicago.com), Chicago Department of Transportation Bicycle Program (www.chicagobikes.org), Census 2000 (www.census2000.gov), Chicago Metropolitan Agency for Planning (www.cmap.illinois.gov), Chicagoland Bicycle Federation (www.biketraffic.org), Chicago Crime (chicagocrime.org), and ESRI Streetmap (http://www.esri.com/). Table 1 shows all variables used in the analysis, their sources, level of specificity, years collected, and manner derived.

Outcome Variables
We used two outcome variables to measure Bike and Ride use, demand and percent occupancy. Each summer during the years 2002, 2003, 2005, and 2006, CTA staff counted the number of bicycles parked at indoor facilities. The counts were done during summer months (June-August), and were always performed on sunny weekdays with high temperatures above 75 degrees. Demand was measured as the number of bicycles parked at each station during the counts. CTA staff did not count some stations on certain years due to station closures (n=2 stations in 2005 and 2 stations in 2006); in these years demand for those stations were assigned missing values. In addition, since there was not a strict methodology for counting at CTA, surveyors considered certain spaces indoors during some years, and outdoors for others (see methods for supply in following paragraph). The demand counts for these stations cannot be disaggregated because there was no way to know which bicycles would have been considered “outdoors” at stations in the years where the status of the spaces changed; we coded demand counts as missing for those stations on those years (n=2 stations in 2005). Finally, staff simply did not count some stations in 2006, and these values were also coded as missing (n=2 stations).

The other outcome variable, percent occupancy, was derived by dividing the demand number by the number of indoor parking spaces (supply). Similar to the demand counts described above, CTA employees performed supply counts of indoor parking spaces at each station for each year of analysis. If there were no indoor parking spaces, then the supply was coded “0” for that station in that year. We coded closed stations as missing. Supply included all spaces that were weather protected and within view of CTA station attendants. Figure 3 shows the one mile buffers around CTA stations and the year that indoor bicycle parking facilities were installed. If there were no indoor spaces at the station during the year of counting, then percent occupancy was coded as missing.

Transit Variables
We calculated the number of bus routes running through each buffer as a proxy for bus service in the area. Two Theme Analyst’s Proximity tool summarized all of the bus routes at each bus stop within the circumference of each buffer. We then counted each unique route, including
those that run only during late nights and rush hours. We then divided the total number of routes by the buffer area, excluding the land uses coded as “water” so as to account for the areas of buffers where buses cannot run (e.g., Lake Michigan), to derive the bus diversity variable. Pace bus service supplements CTA bus service to those stations near and outside Chicago city limits. However, we did not include Pace routes in the derivation of bus diversity for two reasons. First, unlike CTA buses, there is not a reduced transfer fee to switch between Pace buses and CTA rail service. Thus, a rider would have to pay an additional $1.50 instead of $0.20-

Table 1: Environmental Determinants of Bicycling to CTA Rail Stations

<table>
<thead>
<tr>
<th>Outcome Variables</th>
<th>Description</th>
<th>Source</th>
<th>Level of Geography</th>
<th>Years</th>
<th>Manner Derived</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Supply</td>
<td># of indoor spaces supplied at station</td>
<td>Chicago Transit Authority</td>
<td>Station</td>
<td>2002, 2003</td>
<td>Hand counts performed by CTA each summer</td>
</tr>
<tr>
<td>Bus Diversity</td>
<td># of CTA bus routes within buffer divided by square miles within buffer</td>
<td>Chicago Transit Authority (CTA)</td>
<td>Bus Station</td>
<td>2002, 2003, 2005</td>
<td>GeoMap 9.2 Erase and Calculate Geometry tools, ArcView GIS 3.3 Proximity Table tool</td>
</tr>
<tr>
<td>Train Cost</td>
<td>Cost of riding train (in 2005 dollars)</td>
<td>CTA, Consumer Price Index</td>
<td>n/a</td>
<td>2002, 2003</td>
<td>Converted all fares to 2005 dollars based on Consumer Price Index</td>
</tr>
<tr>
<td>Ridership</td>
<td>Average weekday riders at station for month of July (1000s)</td>
<td>Chicago Transit Authority</td>
<td>Station</td>
<td>2002, 2003, 2005</td>
<td>Average weekday ridership reports</td>
</tr>
<tr>
<td>Distance</td>
<td>Average distance (miles) from station to all proximate stations</td>
<td>Chicago Transit Authority</td>
<td>Feet</td>
<td>2002, 2003, 2005</td>
<td>ArcMap 9.2 Measure tool</td>
</tr>
<tr>
<td>Terminus</td>
<td>Is the station a terminus</td>
<td>Chicago Transit Authority</td>
<td>Station</td>
<td>2002, 2003, 2005</td>
<td>Rail maps</td>
</tr>
</tbody>
</table>

Built Environment Variables

<table>
<thead>
<tr>
<th>Source</th>
<th>Level of Geography</th>
<th>Years</th>
<th>Manner Derived</th>
</tr>
</thead>
<tbody>
<tr>
<td>Census</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Emp Density</td>
<td># of housing units per acre</td>
<td></td>
<td>2000</td>
</tr>
<tr>
<td>%Residential</td>
<td>Percentage of land designated residential within buffer</td>
<td>Chicago Metropolitan Agency for Planning</td>
<td>1/2 acre</td>
</tr>
<tr>
<td>%Commercial</td>
<td>Percentage of land designated commercial within buffer</td>
<td>Chicago Metropolitan Agency for Planning</td>
<td>1/2 acre</td>
</tr>
<tr>
<td>%Urban Mix</td>
<td>Percentage of land designated urban mix within buffer</td>
<td>Chicago Metropolitan Agency for Planning</td>
<td>1/2 acre</td>
</tr>
<tr>
<td>%Office</td>
<td>Proportion of land designated office within buffer</td>
<td>Chicago Metropolitan Agency for Planning</td>
<td>1/2 acre</td>
</tr>
<tr>
<td>%Industrial</td>
<td>Proportion of land designated industrial within buffer</td>
<td>Chicago Metropolitan Agency for Planning</td>
<td>1/2 acre</td>
</tr>
<tr>
<td>Entropy</td>
<td>Entropy: Mix of uses for residential, commercial, urban mix, and office</td>
<td>Chicago Metropolitan Agency for Planning</td>
<td>Station Buffer</td>
</tr>
<tr>
<td>Roads</td>
<td>Miles of road within buffer divided by square miles within buffer</td>
<td>ESRI StreetMap 2007</td>
<td>Block</td>
</tr>
</tbody>
</table>

Policy Variables

<table>
<thead>
<tr>
<th>Source</th>
<th>Level of Geography</th>
<th>Years</th>
<th>Manner Derived</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bicycle Lanes</td>
<td>Miles of bike lanes within buffer divided by square miles of buffer within Chicago boundary</td>
<td>Chicagooland Bicycle Federation/CDOT</td>
<td>Street</td>
</tr>
<tr>
<td>Crime</td>
<td>Crimes committed within buffer divided by square miles of buffer within Chicago boundary</td>
<td>Chicago Police Department/Chicago Crime</td>
<td>Block</td>
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</table>

Demographic Variables

<table>
<thead>
<tr>
<th>Source</th>
<th>Level of Geography</th>
<th>Years</th>
<th>Manner Derived</th>
</tr>
</thead>
<tbody>
<tr>
<td>%African American</td>
<td>Percent African American within one mile buffer of station</td>
<td>Census 2000</td>
<td>Block Group</td>
</tr>
<tr>
<td>%Hispanic</td>
<td>Percent Hispanic within one mile buffer of station</td>
<td>Census 2000</td>
<td>Block Group</td>
</tr>
<tr>
<td>Median Income</td>
<td>Median income ($1,000) of households within one mile of the station</td>
<td>Census 2000</td>
<td>Block Group</td>
</tr>
<tr>
<td>%High School</td>
<td>High school or higher within one mile buffer of station</td>
<td>Census 2000</td>
<td>Block Group</td>
</tr>
</tbody>
</table>
Figure 3: Year Bicycle Parking Installed

Legend

Year Bicycle Parking Installed
- ♦ No Bicycle Racks
- ▲ Since 2006
- ★ Since 2005
- □ Since 2003
- ● Since 2002

City Boundary
One mile buffer
$0.25. Second, the frequency of service of Pace buses is generally much lower than those of CTA buses.

We calculated the cost of riding the train for each year in 2006 dollars, using the consumer price index for inflation. CTA uses a flat fare, so cost is the same across all stations in a given year.

Average number of weekday train riders per station was calculated as the number, in thousands, of people who boarded at each station during the month of July of each year. These numbers were derived from CTA ridership reports as measured by turnstile counts.

Using ArcMap® GIS 9.2, we calculated the average distance from a given station, in miles, to all proximate stations on either side. If a station served more than one line, then we included the proximate stations of all lines in calculating the average (see Figure 1). For the Howard and Belmont stations, we did not include the distance between these two stations, as served by the Purple Line Express, since technically a rider could ride the train from one of the significantly closer stations using a different train line. Similarly, we did not include the distance to the Skokie station from the Howard station in the calculation for Howard station.

Finally, we created a dichotomous variable to describe whether the station was a terminus, indicating that it was situated at the end of a rail line. We did not consider stations that were the end of some lines, but in the middle of others, such as Belmont and Howard, as termini.

**Built Environment Variables**

We derived a number of variables to serve as proxies for built environment characteristics that might be related to bicycling to transit. Within each station buffer, we calculated residential density and employment density with Census 2000 data, using Two Theme Analyst’s Area Percentage Tool to calculate the median income for each buffer. This tool calculates the area for each block group (or portion of block group) residing within the station buffer and then creates a proportion of that area compared with the total station buffer area. The tool then multiplies the proportion of area by the residential or employment density value for that block group. By aggregating these values, we calculated the respective densities for each buffer. To improve the accuracy of this estimate, we first removed land areas labeled as water (e.g., Lake Michigan, rivers, etc.) or major roads (e.g., highways) using ArcMap® 9.2’s Erase tool in order to limit the error of calculating land where no people are able to have residences. In addition, we used a similar process to create several variables to describe land uses. For each buffer, we calculated the percent of space for each buffer dedicated to residential, commercial, urban mix, office, and industrial. Urban mix was defined as a mix of smaller retail and office/professional uses such as grocery stores, department stores, and eating and drinking establishments.

For each station buffer we also sought to examine the mixing of land uses. We created an entropy score from the percentage of residential, commercial, urban mix, and office land use variables created through the method described above. The formula for entropy is described in Table 1. An entropy score of 1 indicates a completely even mix of all uses; a score of 0 indicates a single type of use within the buffer.
In order to measure connectivity, we divided miles of roads within a buffer by the total area in the buffer. As with the bus diversity measure, land labeled as “water” was excluded from the total area calculation.

**Policy Variables**

We derived a variable indicating the density of bicycle lanes in each buffer using data from the Chicagoland Bicycle Federation (CBF) and Chicago Department of Transportation (CDOT). GIS database files indicated the year in which each bicycle lane was installed in the city. With this information, we calculated bicycle lane mileage for each year of analysis. Since the data only included bicycle lanes within Chicago City limits, we divided the mileage by the amount of buffer area within the city limits to serve as a valid bicycle lane density variable (Figure 4). If less than 0.1 square miles of buffer area was located in the city, we assigned it a missing value (n=14, with 56 observations over the 4 years).

We calculated a crime variable with data from the Chicago Police Department, formatted by Chicago Crime. We geocoded all crimes within the Chicago city limits from November 2005 through December 2006. Similar to the methods for deriving bicycle lane density, we then divided this count by the amount of buffer area residing within the city limit to derive a crime density variable.

**Demographic Variables**

We calculated four demographic variables using Census 2000 data to measure the racial and socioeconomic make-up of the station neighborhoods. We used the Two Theme Analyst Extension’s Aggregate Data tool in ArcView® GIS 3.3 to calculate the total number of African Americans, Hispanics, and population having completed high school or higher living within each station buffer. We then divided the totals by the number of residents living within each buffer to create the percentage variables: %African American, %Hispanic, and %high school (for %high school, we divided the total by the number of residents aged 25 or older living in the buffer). There was some overlap in the population of African Americans and Hispanics in each buffer, but Census 2000 data indicated that within Cook County, only 1.39% of those reporting being Hispanic/Latino indicated their race as black alone. Similarly, only 1.07% of those reporting their race as black alone also indicated being Hispanic/Latino.

To calculate median income, we used Two Theme Analyst’s Area Percentage tool with a similar method as calculating residential and employment densities described above.

**Analytical Methods**

**Regression Models**

Because Bike and Ride participation variables are based on count data which vary over time, we estimated a number of count models, using panel methods. Using Stata®/SE Version 10, we first estimated three longitudinal negative binomial regressions (xtnbreg function), using demand counts as the outcome variable (Cameron & Trivedi, 1998; Hausman, Hall, & Griliches, 1984; Liang & Zeger, 1986). The longitudinal function is similar to a cross-sectional negative binomial regression, but it accounts for the use of the same stations over time. Each station
Figure 4: On Street Bicycle Lanes and Off-Street Trails in City of Chicago, 2002-2006.
used in the analysis had non-missing values for all input variables and the outcome variable (n=129, with 510 observations). The first model used demographic and transit variables as the input variables.

The second model used the input variables that had a coefficient with p<0.15 significance in the first model as well as the built environment variables. We employed those variables that had a coefficient with a p<0.15 significance in the third, preferred model, along with the policy variables (bicycle lanes and crime). We ran random effects and fixed effects models for each procedure, and a Hausman test determined the appropriate model for analysis (Noland & Karlaftis, 2005).

For the percent occupancy outcome variable, conditional on having supply, we estimated three longitudinal linear ordinary least squares regression models (xtreg command in Stata) (Baum, 2006; Dwyer & Feinleib, 1992). Stations used in the analysis had non-missing values for all input variables and the outcome variable (n=62, with 159 observations). Since parking supply is already accounted for in the outcome variable, it was not used as an input variable in these models. We generated random and fixed effects models, and a Hausman test determined the appropriate model for interpretation (Baum, 2006). We only used those variables that had a p<0.15 significance in each model in subsequent models.

Since environmental data tend to covary, we calculated VIF (variance inflation factor) scores in linear regression models using the percent occupancy outcome variable in the year 2006. We eliminated collinear variables one at a time, and the models were run until all VIF scores greater than 20 were eliminated for 2006. VIF scores were then calculated for the remaining variables for the other three years.

Results

Both the number of indoor bicycle parking spaces and their use grew significantly during the data collection period, as shown in Figures 5-9. The number of spaces increased by 225% over that time period, and parking at those spaces increased by 400%. However, the increase in use of the facilities was uneven. For example, an aggregation of values at Orange Line stations, located on the southwest side of the city (see Figure 1), show a greater than 80% occupancy during each count while a similar aggregation of values for Green Line stations, located on both the due west and due south sides of the city, revealed less than 25% occupancy each year.

Table 2 shows the difference in variable values between 2002 and 2006. Bicycle lane density increased by an average of 68% over the time period, whereas diversity of buses decreased by an average of 0.3 routes per square mile of buffer over the time period. The cost of train fare increased by $0.25 between 2002 and 2003, but in 2006 dollars, the increase was only $0.07 from 2002 to 2006. We attribute the small difference in values for cross-sectional variables to the slightly smaller n value in 2006 versus 2002.

Results of Demand Count Negative Binomial Regression Models

We eliminated the following variables from the analysis because they showed VIF scores greater than 20 in 2006: percent of residents having completed high school or higher, employ-
Figure 5: Number of CTA Stations with Indoor Bicycle Parking Facilities, 2002-2006 (Total = 143 Stations)
Figure 6: Number of Interior Bicycle Parking Spaces at CTA Rail Stations and Usage, 2002-2006

Figure 7: Number of Interior Bicycle Parking Spaces at CTA Red Line Rail Stations and Usage, 2002-2006
Figure 8: Number of Interior Bicycle Parking Spaces at CTA Orange Line Rail Stations and Usage, 2002-2006

Figure 9: Number of Interior Bicycle Parking Spaces at CTA Green Line Rail Stations and Usage, 2002-2006
ment density, percentage office land use, percentage residential land use, and entropy. The remaining variables all had average VIF scores of 10 or lower for the years 2003, 2005, and 2006, and an average of less than 15 over all four years, with the exception of percentage African American, which had an average VIF score of 24 during 2003, 2005, and 2006 and average score of 38 over the four years. Due to an a priori expectation of the strong influence of the percentage of African Americans in a neighborhood, and due to the varying contributors to its multicollinearity score, we retained the variable for analysis.

Table 3 demonstrates the outcomes of the three negative binomial regression models. In each model, we found significant evidence that using panel data regression methods were appropriate ($G^2 \geq 8.61$), and the equations were statistically significant ($p<0.01$). We found significant evidence of overdispersion for the variables in the preferred model ($G^2 > 22.52$, $p<0.001$) when used in the cross-sectional negative binomial regression model for 2006, indicating that the negative binomial regression model is preferred over the Poisson regression model (Long & Freese, 2001). The Hausman test indicated the adequacy of a random effects model ($p>0.05$) for all three iterations of the model.

A number of the socioeconomic and transit network variables were statistically associated with
Table 3: Random Effects Longitudinal Negative Binomial Regression Models of Number of Bicycles Parked at CTA rail stations (Demand – n=510)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Preferred Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>coeff</td>
<td>e*coeff</td>
<td>%change</td>
</tr>
<tr>
<td>%African American</td>
<td>-0.03***</td>
<td>0.97</td>
<td>-2.84</td>
</tr>
<tr>
<td>Median Income</td>
<td>-0.05***</td>
<td>0.95</td>
<td>-4.63</td>
</tr>
<tr>
<td>Supply</td>
<td>0.29***</td>
<td>1.33</td>
<td>33.25</td>
</tr>
<tr>
<td>Bus Diversity</td>
<td>-0.12***</td>
<td>0.89</td>
<td>-11.31</td>
</tr>
<tr>
<td>Ridership</td>
<td>0.21***</td>
<td>1.24</td>
<td>23.81</td>
</tr>
<tr>
<td>Terminals</td>
<td>-0.01</td>
<td>0.40</td>
<td>-59.90</td>
</tr>
<tr>
<td>%Hispanic</td>
<td>0.00</td>
<td>1.00</td>
<td>0.54</td>
</tr>
<tr>
<td>Train Cost</td>
<td>0.53</td>
<td>1.69</td>
<td>69.30</td>
</tr>
<tr>
<td>Distance</td>
<td>0.39</td>
<td>1.47</td>
<td>47.00</td>
</tr>
<tr>
<td>Res Density</td>
<td>0.00</td>
<td>1.00</td>
<td>-0.24</td>
</tr>
<tr>
<td>%Commercial</td>
<td>0.09</td>
<td>1.10</td>
<td>9.65</td>
</tr>
<tr>
<td>%Urban Mix</td>
<td>-0.03</td>
<td>0.97</td>
<td>-2.66</td>
</tr>
<tr>
<td>%Industrial</td>
<td>-0.01</td>
<td>0.99</td>
<td>-0.73</td>
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<tr>
<td>Roads</td>
<td>-0.01</td>
<td>0.99</td>
<td>-0.64</td>
</tr>
<tr>
<td>Bicycle Lanes</td>
<td>0.18</td>
<td>1.20</td>
<td>20.31</td>
</tr>
<tr>
<td>Length</td>
<td>-0.47***</td>
<td>0.62</td>
<td>-37.60</td>
</tr>
</tbody>
</table>

Model Statistics:
- Wald Chi-square (p<0.01)
- Log likelihood (p<0.01)
- Log likelihood-ratio test vs. pooled: chi-bar-square (p<0.01)
- Hausman Test chi sq (p<0.01)

* p<0.1
** p<0.05
*** p<0.01
the number of bicycles parked at the facilities. To interpret the coefficients in the negative binomial models, we used the exponential function to calculate $e^x$, where $x$ is the coefficient in each model. Then, we subtracted 1 from $e^x$ and multiplied by 100. The resulting number is the percent change in the outcome variable given a one unit change in the input variable.

In the preferred model, we estimated that an increase of one route per square mile corresponded to a decrease in demand by 8.35% ($p<0.05$), terminus status correlated with a 75% decrease in demand ($p<0.05$), and an increase of 1,000 crimes per square city mile was related with a 37.60% decrease in bicycle parking demand ($p<0.01$). Supply was positively associated with the outcome variable, with an increase of one parking space related to a 32% increase in demand ($p<0.01$), as was ridership, with an increase of 1,000 weekday riders at a station corresponding with a 28% increase in bicycle parking ($p<0.01$). Two demographic variables, percent African American and median income, had an significant inverse correlation with the number of bicycles parked indoors at rail station.

Percent occupancy models

Table 4 shows the results from the three linear regression models. The results from the preferred model ("$r^2$ overall") suggest that at least 50% of the variation in percent occupancy between the stations can be explained by the variation in the coefficients of the models. The "$r^2$ within" values for all models were 0.02 or lower for all models. This indicates that little of the variation in the percent occupation could be explained by the change in years. This was supported by the higher "$r^2$ between" values for all the models (0.64 or greater). The Hausman test indicated the suitability of a random effects model for each iteration ($p>0.05$).

The coefficients in the linear regression models estimate the percent change in percent occupancy given a one unit increase in the variable. The preferred model suggests that an extra bus route per square mile of buffer area is related to a 3.04% decrease in percent occupancy. Similarly, residential density was correlated with a decrease in percent occupancy ($p<0.05$). Ridership was the only significant variable positively associated with an increase in percent occupancy, with a 2.63% increase per 1,000 passenger increase ($p<0.01$). A one percent increase in African American population within the buffer corresponds with a 4.57% decrease in percent occupancy ($p<0.01$).

Discussion

Our results indicate that several environmental characteristics are related to Bike and Ride behavior, even when accounting for demographic variation between neighborhoods. In accordance with previous work, Bike and Ride participation, as measured in two ways using counts of parked bicycles, was higher at stations with higher numbers of train riders, fewer bus options and more bicycle parking spaces. Surprisingly, participation was lower in areas with higher residential density and higher percentages of African American residents. Despite theoretical and empirical support for the importance of other environmental factors, we found no significant associations between program participation and land use, miles of road or density of bicycle lanes. However, post-estimation analyses shown later in this section do indicate that a combined policy approach, focused on multiple factors related to Bike and Ride participation, will generate the most efficient increase in program use.
### Table 4: Random Effects Longitudinal Linear Regression Models for Environmental Determinants of Percent Occupancy of Indoor Bicycle Parking Facilities at CTA Rail Stations (n=159)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1</th>
<th></th>
<th></th>
<th></th>
<th>Model 2</th>
<th></th>
<th></th>
<th></th>
<th>Preferred Model</th>
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<tr>
<td></td>
<td>coeff</td>
<td>std error</td>
<td>z</td>
<td></td>
<td>coeff</td>
<td>std error</td>
<td>z</td>
<td></td>
<td>coeff</td>
<td>std error</td>
<td>z</td>
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<td>%African American</td>
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<td>-3.46</td>
<td></td>
<td>-0.76***</td>
<td>0.12</td>
<td>-6.09</td>
<td></td>
<td>-0.60***</td>
<td>0.13</td>
<td>-4.57</td>
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<td>Bus Diversity</td>
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<td>1.08</td>
<td>-2.28</td>
<td></td>
<td>-3.42***</td>
<td>1.06</td>
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<td></td>
<td>-3.24***</td>
<td>1.07</td>
<td>-3.04</td>
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<tr>
<td>Ridership</td>
<td>3.94***</td>
<td>1.50</td>
<td>2.63</td>
<td></td>
<td>3.36***</td>
<td>1.33</td>
<td>2.52</td>
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<td>Distance</td>
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<td>%Hispanic</td>
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<tr>
<td>Median Income</td>
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<tr>
<td>Terminus</td>
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<td>13.64</td>
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<td></td>
</tr>
<tr>
<td>Res Density</td>
<td></td>
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<td></td>
<td>-1.22***</td>
<td>0.60</td>
<td>-2.01</td>
<td></td>
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<td>-1.13***</td>
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<td>-2.06</td>
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<tr>
<td>%Commercial</td>
<td></td>
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<td></td>
<td>-4.24</td>
<td>9.21</td>
<td>-0.46</td>
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<td></td>
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</tr>
<tr>
<td>%Urban Mix</td>
<td></td>
<td></td>
<td></td>
<td>-1.21</td>
<td>1.38</td>
<td>-0.88</td>
<td></td>
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</tr>
<tr>
<td>%Industrial</td>
<td></td>
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<td>0.03</td>
<td>0.40</td>
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<tr>
<td>Roads</td>
<td></td>
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<td>2.18</td>
<td>1.78</td>
<td>1.23</td>
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<tr>
<td>Bicycle Lanes</td>
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<td>-2.44</td>
<td>5.37</td>
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<tr>
<td>Crime</td>
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<td>-5.02</td>
<td>3.60</td>
<td>-1.39</td>
<td></td>
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**Model Statistics**

<table>
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<tr>
<th></th>
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<th>Model 2</th>
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<th></th>
<th></th>
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<td>$r^2$ Within</td>
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<td></td>
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<td>$r^2$ Between</td>
<td>0.64</td>
<td></td>
<td></td>
<td></td>
<td>0.66</td>
<td></td>
<td></td>
<td></td>
<td>0.64</td>
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</tr>
<tr>
<td>$r^2$ Overall</td>
<td>0.51</td>
<td></td>
<td></td>
<td></td>
<td>0.52</td>
<td></td>
<td></td>
<td></td>
<td>0.51</td>
<td></td>
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</tr>
<tr>
<td>Wald Chi-square</td>
<td>117.96 (p&lt;0.01)</td>
<td></td>
<td></td>
<td></td>
<td>120.19 (p&lt;0.01)</td>
<td></td>
<td></td>
<td></td>
<td>114.35 (p&lt;0.01)</td>
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<tr>
<td>Hausman Test chi-sq</td>
<td>p&gt;0.53</td>
<td></td>
<td></td>
<td></td>
<td>p&gt;0.96</td>
<td></td>
<td></td>
<td></td>
<td>p&gt;0.14</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* p<0.1
** p<0.05
*** p<0.01
Explanations of Environmental Influences

Assuming ridership is an indication of “attraction,” the relationship between weekday boardings and facility use supports the idea that the “attraction” of high transit use stations could increase cycling in the area (McNally, 2000). Increasing bicycle parking at stations with high ridership and a number of popular nearby destinations may further enhance use of the mixed modes of transport. The association of higher Bike and Ride use with lower levels of bus service and longer distances to rail stations supports the idea that people will choose bicycling when walking and taking the bus are more onerous options. While our analysis was not designed to determine whether these Bike and Ride participants would commute in personal cars if the program was not available, it does allow for this supposition on certain days, and provides an avenue for future research.

The inverse correlation between buses and cycling in this context reveals the complex relationship of the two modes. In one component of the Bike and Ride program, buses carry bicycles on racks. In this way, they are complementary, and policies promoting one mode will support the other. However, in terms of arriving at rail stations, riding the bus and bicycling may compete with each other in mode choice decision. High bus density in a neighborhood may make it difficult to bicycle, and create conflicts between cyclists and buses. Thus, policy-makers and transit professionals should search for context-sensitive solutions in different neighborhoods. In areas where there is significant bus service, they should search for ways for bicycles and busses to more safely coexist. In areas with minimal bus service, bicycle supports and facilities may be a much more cost effective way to promote alternative modes of transport.

The inverse relationship between residential density and Bike and Ride usage was surprising, particularly because the input variable is an indication of total population in the buffer. This finding may highlight the specific needs of bicycle trips, which could be better fostered by a less dense or urban built environment with fewer impediments and dangers (Barnes & Krizek, 2005). The negative association of crime with number of bicycles parked at stations supports the premise that people are less likely to feel safe leaving their bicycles at a station in neighborhoods with significant crime, even if it is within view of station attendants. Thus, attention to safety at and around stations is important for policymakers.

The significant negative association of the percent of African Americans living in a station neighborhood with both variables describing Bike and Ride use was also unexpected given previous findings which showed that African Americans are more likely to use transit (Pucher & Renne, 2003). However, the negative association of median income with Bike and Ride demand supports previous studies (Barnes & Krizek, 2005; M. Winters et al., 2007). These findings may reflect the complex interaction of demographics with bicycling and transit. Characteristics of a neighborhood (and people living within that neighborhood) that are conducive to taking transit may not apply to cycling. Similarly, the reasons a person might enjoy cycling in her neighborhood might not be the same as why she would choose to ride transit. In addition, the high collinearity between percent African American and a number of the input variables (e.g., bus density, residential density, crime, median income, urban mix) could mean that the variable is an indicator of other environmental influences negatively associated with the outcome variables.
Our use of the environment (neighborhood characteristics) instead of individual characteristics may also help explain the demographic influences. The independent variables in this study do not describe the Bike and Ride users, but rather the neighborhoods surrounding stations. Even though African Americans are more likely to use transit and thus could be amenable to Bike and Ride (Pucher & Renne, 2003), the environment in higher percentage African American neighborhoods may be less conducive to the behavior independent of individual preference. Since the outcome count variable is very small in comparison to the population, it is hard to test this hypothesis with these data. However, these findings do provide evidence of the importance of separating environmental influences from individual preferences in future research.

Not surprisingly, we found a significant correlation between bicycle parking supply and demand. Initially, CTA built bicycle parking facilities at stations based on perceived demand, equity across stations, and sufficiency of space (A. Malick, personal communication, February 14, 2008). The Chicago Department of Transportation installed the parking facilities at no cost to CTA if the stations were located inside the city limits. After 2003, CTA prioritized stations based primarily on space, and a concerted effort was made to install racks at all stations with sufficient area. If demand and space were sufficient, additional parking facilities were added to stations with previously existing spaces. Since the rationale for installing the facilities was largely independent of perceived demand in later years but was related to demand in earlier years (which we found to be related to demand in later years), there could be a causative association between supply and demand that could be further investigated. With the current analysis, we cannot isolate whether the supply of parking racks generated demand or not.

The lack of a significant association between any of the land use percentage variables or road miles with either outcome variable is consistent with previous findings which only found a moderate effect of the built environment on cycling (Moudon et al., 2005). The non-significant relationship between bicycle lanes and the use of indoor parking can be partially explained by studies which found that people will only use bicycle lanes if they live quite close to them (Krizek & Johnson, 2006; Schneider, 2005). Since the one mile buffers are relatively large, the majority of residents in each one likely do not live adjacent to the on-street bicycle lanes (Figure 4), perhaps diminishing their impact in the analysis. In addition, the Chicago Department of Transportation Bicycle Program created on-street bicycle lanes based on a combination of demand, neighborhood equity, and opportunistic collaboration with street improvement projects (D. Gleason, personal communication, December 17, 2007). In recent years, prioritization has focused on completing a citywide bicycle network, independent of demand. Since the network may not necessarily go near every station, the completion priority may be more effective for longer distance cycling that does not necessarily include stations as destinations. Furthermore, the influence of bicycle lanes on traveling to transit may grow over time, once the network is more complete. Transportation professionals should consider the proximity of stations when planning the construction of bicycle lane networks.

**1+1=3: The Effects of Simultaneous Solutions**

In spite of the statistical significance of many of the influences we examined, small coefficient values and post-estimation analysis reveal that each individual variable has a limited impact on the total number of bicycles parked at stations. For example, if all variables are held at their
Figure 10: Negative Binomial Regression Estimation of Number of Bicycles Parked at CTA Rail Stations Based on Supply

- All Other Variables held at Mean Values
- Crime at 20% value and bicycle lanes at 80% value. All other variables held at mean values.
- Crime and bus diversity set to 20% values, bicycle lanes and ridership set to 80% values. All other variables held at mean values.
mean values, our analysis predicts that adding four parking spaces to a station with only two spaces generates an increase of 0.4 bicycles parked at that station. Our results, however, also suggest that the influence of parking supply on demand is enhanced as more parking spaces are added. If we add ten parking spaces instead of four, we would predict an increase of nearly three parked bicycles (Figure 10).

Furthermore, a comprehensive suite of solutions, targeting multiple factors, may yield even more impressive results. If our addition of ten parking spaces were accompanied by an increase in bicycle lanes to the 80th percentile level and a decrease in crime to the 20th percentile level, our analysis predicts an increase of nearly six, rather than three, bicycles parked at the station. The same changes, when occurring at a “high attraction” station (80th percentile for ridership) with limited bus access (20th percentile for bus diversity), yields nearly 11 additional Bike and Ride users, more than the increase in parking spaces. The success of approaches which change multiple factors at once is consistent with previous findings (Pucher & Buehler, 2006). It is interesting to note that an increase in supply from 2 to 6 on the third curve only yields an estimated 1.5 more bicycles parked at the station. This indicates that there may be a critical mass that must be reached in bicycle facilities and other factors in order for significant results to occur.

In Chicago, indoor bicycle parking is just one component of the Bike and Ride program. It is likely that as the other two parts of the program (bikes on buses and bikes on trains) become more popular, more people will use the parking spaces. For example, in 2006, there were two bicycles parked at the O’Hare station, where there is no road to access the station via bicycle. Thus, the travelers must have bicycled to a station other than O’Hare, perhaps one without indoor parking, brought their bicycles on the train, and then parked them at the O’Hare station after alighting. This indicates the appeal of a complete alternative transportation network with benefits that increase exponentially with time.

Cities outside of the United States serve as examples of successful comprehensive programs. For example, Transport for London reported an 83% increase in cycling in the city since 2000, due in part to the nearly 900 kilometers in bicycle lanes set to be completed by 2010 (Transport for London, 2008). In addition, commuter cycling in the central business district of London has increased by 16% following the implementation of a charge for driving a vehicle into the area (London cycling campaign, 2008). The city aims to increase bicycle use by spending $1 Billion on its new bicycle share program, where people can rent bicycles affordably throughout the city using electronic cards (Reuters, 2008). The rental program is based on the “Velib” bicycles in Paris, which reported 3.7 million rides in its first two months of existence and has changed the way many get around the city (Beardsley, 2007).

Continuation and enhancement of current efforts by the city of Chicago could generate results similar to those of London. There are over 10,000 bicycle parking spaces in Chicago, more than any other city in the US (Mayor's Bicycle Advisory Council, 2006). In 2004, the City of Chicago opened the Millennium Park Bicycle Station, now called the McDonald’s Cycle Center, with much fanfare. The facility offers secure indoor parking, locker and shower facilities, and bicycle repair, and has proven to be quite successful, in spite of its less than ideal location for commuters. A similar facility closer to a transit hub could further increase use of such a facil-
ity along with the use of *Bike and Ride* facilities. Development of such a facility could be coor-
dinated with other city initiatives, such as tourism, in order to attract new and visiting riders to
promote economic development (Meletiou et al., 2005). Other Chicago DOT initiatives, such as
increasing the visibility of bicycle routes and completing the bicycle lane network, will comple-
ment the *Bike and Ride* program and cycling and alternative transportation modes overall. In
addition, strong partnerships between the City of Chicago Department of Transportation, CTA,
and Chicagoland Bicycle Federation (the local advocacy group) continue to bring about leader-
ship in these areas of transportation. Longitudinal and objective evaluation of these programs,
similar to the analyses presented here, can help determine program success and guide planners
in their efforts to facilitate alternative transportation in Chicago and other cities.

**Limitations**

Even though CTA collected data over four years, the analyses involved a relatively small sam-
ple size of only 62 unique stations for the linear regression models, due to the high number of
“0” values for supply, and 129 stations for the negative binomial regression models with a count outcome. Only 19 of the stations had indoor bicycle parking in 2002, and still less than half of all stations had facilities for inclusion in the regression analysis in 2006. In addition, de-
mand counts were relatively low, with a maximum of 19 parked bicycles and an overall mean
of less than one. Nevertheless, the stations included in all analyses cover every rail line and
geographic directions of the city; thus, we feel they are representative of the varying neighbor-
hoods in Chicago.

In addition, while the longitudinal nature of the data in this study provides a new contribution to
the literature, the time frame for the analysis was only four observations over the five initial
years of the existence of the facilities. Barnes and Krizek (2005) noted that the relatively large
confidence intervals of single observations combined with small sample sizes of cyclists can
skew models. Follow-up studies with more years and observations could examine the long-term
effects of the program which might not be revealed in a short time frame with few observations.
Since CTA and CDOT have prepared a *Bike and Ride* marketing plan and program, we recom-

mend this type of follow-up study to evaluate their results.

There was not a consistent counting methodology between years at CTA, and some observa-
tions were lost due to this inconsistency. Nevertheless, the demand count of bicycles parked at
CTA stations provides an objective outcome variable for use of the parking spots and bicycling
behavior. This is unique in bicycling research, which mostly relies on subjective recall data to
determine the number of cyclists using facilities (Dill & Carr, 2003; Hoehner et al., 2005; M.
Winters et al., 2007).

Furthermore, we do not know if people who parked their bicycles at the stations on the days of
the counts actually did take the train, though CTA’s surveys had indicated that most people who
parked their bicycles do ride the train. Many of the parking spots are located after the turnstiles,
and it is likely safe to assume that nearly all of these travelers would not pay the train fare sim-
ply to have a space to park their bicycle.

A final limitation of the study was the lack of bicycle lane and crime data outside the City of
Chicago. This caused the values of 14 different stations (56 observations) to be excluded from
all analyses. Most importantly, a few of the terminal stations were excluded from the analysis which may have biased the contribution of this variable to the models. When estimating the preferred negative binomial regression model while dropping the bicycle lane and crime data, the terminus variable is longer statistically significant (p>0.2), and the direction of the coefficient becomes positive.

**Conclusion**

This study shows that complementary policy efforts can increase the rates of bicycling to transit and ensure more consistent use of this mode of travel across different neighborhoods. When the environmental context is sufficiently conducive to bicycling to transit, the presence of indoor bicycle parking facilities appears to increase the catchment area of the station. Thus, programs like Bike and Ride should be strongly considered by transit and DOT planners and other policy decision makers, especially given the significantly lower cost of installing bicycle parking versus extending the transit network. Indoor parking facilities at rail stations seem to make the most impact in less dense neighborhoods conducive to bicycling, especially if the rail station is well utilized.

However, these facilities will be more successful if implemented in tandem with other policies supportive of bicycle to transit behavior. When extending the network of on street bicycle facilities, planners should ensure that they are built near rail stations to fully leverage both the bicycle lanes and any transit related facilities. In addition, crime in neighborhoods around stations should be addressed in order to further cycling and transit use.

Finally, this study shows a cost-effective way for transit agencies to collect longitudinal data. Planning practitioners should take initiative in monitoring and evaluating programs to strengthen arguments for alternative modes of transportation. Researchers should continue to explore the built environment’s potential influence on bicycling to transit.
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