DIMENSIONS OF DIVVY

Exploring the social, spatial and temporal performance of bikesharing in a period of growth and expansion

BY C. SCOTT SMITH, PH.D. & RILEY O'NEIL

FEBRUARY 15, 2018

2018

Chaddick Institute for Metropolitan Development at DePaul University

STUDY TEAM

AUTHORS	C. SCOTT SMITH* AND RILEY O'NEIL**
DATA COLLECTION	MALLORY LIVINGSTON AND STIJN VAN DER SLOT
GRAPHICS	C. SCOTT SMITH
PHOTOGRAPHY	C. SCOTT SMITH, DIVVY

*CORRESPONDING AUTHOR & ASSISTANT DIRECTOR, CHADDICK INSTITUTE

** TWELVE TONE CONSULTING

CONTACT: C. SCOTT SMITH, PHD | PHONE: 312.362.5770 | EMAIL: chaddick@depaul.edu

Numerous studies over the past two decades have found clear evidence that vibrant communities are inextricably linked with opportunities for active and/or non-motorized transportation. Indeed, pedestrian and bicycling facilities, when purposively linked with mixed land uses and public transit, can become critical components of safe, healthy and enjoyable places.

A synergetic force working within the broader movement of active transportation is the emergence, widespread diffusion and expansion of public bicycle sharing systems (BSS). Such systems—which make bicycles available to the general public on an as-needed basis—have undergone several refinements over the past five decades and, in recent years, have dramatically changed the ecology of urban and, increasingly, *sub*urban transport.

This four-part study summarizes general aspects of bikeshare planning and explores various social, spatial and temporal dimensions of Chicago's Divvy bikeshare system, specifically. The report is organized as follows:

SECTION I *briefly traces the evolution of public bikesharing and summarizes how the practice of planning bikeshare systems has changed over time.*

SECTION II *characterizes the three phases of Chicago's Divvy system beginning with its initial rollout in 2013 through its first and second expansions, in 2015 and 2016, respectively, paying special attention to service and performance gaps.*

SECTION III *develops a series of statistical models designed to identify factors that best explain variations in Divvy system usage at the station level.*

SECTION IV *discusses recent and proposed changes to Chicago's Divvy system and concludes with potential implications for bikeshare planning, more generally.*

I. EVOLUTION OF PUBLIC BIKESHARE SYSTEMS AND PLANNING

DEVELOPMENT OF US BIKESHARE SYSTEMS

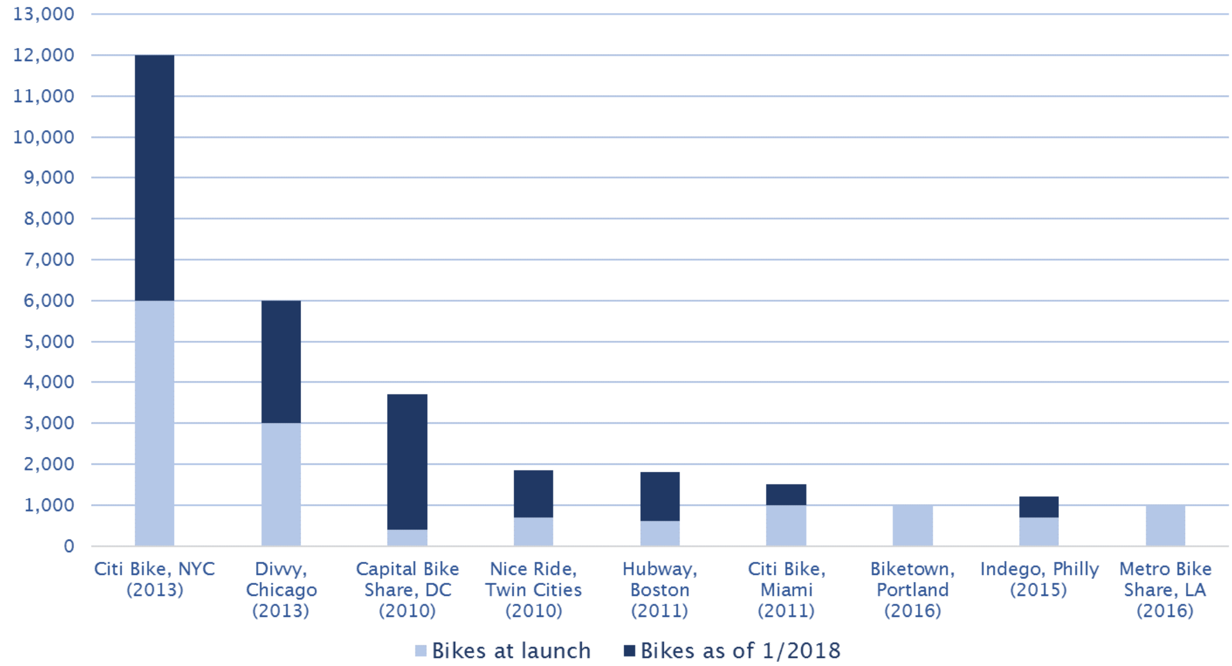
Later-generation public bicycle sharing systems (BSS)—which provide users short-term access to bicycles via automated docking stations or on-bike interfaces—are increasingly seen as an innovative way to advance active transportation and facilitate intermodal connections in urban and, increasingly, suburban areas.

The popularity of bicycle sharing is most clearly evidenced by the quickening pace of BSS investments by cities, non-profits and private entities throughout Europe, Asia and, more recently, North America. A 2016 assessment estimates that there are over one thousand public use bicycle sharing systems globally; supplying a combined 2.2 billion bicycles. And while over one third of these programs are located in China, the number of systems in Europe (524) and North America (121) is growing steadily (*1*).

Late-comers to BSS, US cities began to build out their modern bikeshare infrastructure in the early 2010s. The three largest systems—Citi Bike in New York City (with 12,000 bicycles), Divvy in Chicago (6,000 bicycles) and Capital Bikeshare in Washington DC (3,700 bicycles)—began service in May 2013, June 2013 and May 2010, respectively and have expanded considerably over time (Figure 1). Data from the National Association of City Transportation Officials (NATO) estimates that US cities logged over 88 million trips since 2010 and added 24 public bikeshare systems between 2015 and 2016 alone (*2*).

One explanation for the rapid adoption and diffusion of BSS is that contemporary programs have largely overcome many of the technical challenges that constrained widespread use of earlier-generation systems. Contemporary bikeshare programs are characterized by: *improved methods of (re)distribution* (or rebalancing bikes to meet diurnal variations in supply and demand); *ease of installation* (e.g., use of solar on station kiosks no longer require expensive and time-consuming underground electrical wiring); *better bicycle design* (e.g., stations

Figure 1. Largest US Bikeshare Systems and Expansions as of January, 2018



and bicycles have secure locking mechanisms); *smartcard and credit card usage* which eliminates anonymity and reduces vandalism; *ease of customer use* via automated payment and checkout systems as well as mobile apps that make it easy to identify bicycle and station location and bicycle availability in real time; and *creative business models* (e.g., many BSS are public-private partnerships that leverage short-term federal capital investments with longer-term investments by local governments and nonprofit entities) that allow for the implementation of a wide range of system types and purposes (*3*, *4*). Emerging technological advancements in bikeshare include integration of electronic bikes, dockless systems and improved integration with public transport via inter-agency/modal transit cards (*5*).

In addition to the above technological and supply-side improvements, BSS have also been bolstered by demand-side trends including demographic shifts and preferences in the US population that favor (re)urbanization, active transportation (within both urban and suburban settings as well as across socio-demographic groups) and an overall willingness to participate in sharing economies connected via mobile technologies (*6*–*11*).

EVOLUTION OF BIKESHARE PLANNING

The initial rollout of BSS in the US relied only marginally on conventional models of transportation planning in part because planners lacked the necessary information to adequately forecast demand for this new mode of transport (e.g., bicycle counts and surveys). As a result, planners were compelled to swiftly familiarize themselves with the technology of BSS, negotiate suitable business models with stakeholders and investors, identify optimal system sizes and scopes and, when planning for dock-based systems, determine—oftentimes with considerable input from the broader community—locations for bikesharing stations that would best serve stakeholders and leverage the existing transportation network (*12*).

Some cities followed a more conservative and measured approach toward system implementation; opting to delay development to allow time for feasibility analyses and more extensive periods of public input (e.g., Philadelphia, Portland and Los Angeles). Other cities forged ahead quickly, adopting a higher-risk, "fail-fast" approach typical of technology start-ups (*13*). In some cases, the latter approach led to some failures such as the Orange County Transit Authority's Fullerton and Seattle's

Pronto systems. Nonetheless, the initial surge of BSS adoption in US cities over the past eight years has also dramatically elevated the visibility and role of active transportation in urban areas within a relatively short period of time.

Concurrent with and in response to this rapid expansion of and interest in BSS was the drafting of technical guides and tools to assist cities with the strategic planning of public bikeshare systems. One of the earliest such reports, Bike Sharing in the United States by the Toole Design Group (TDG) and Pedestrian and Bicycle Information Center (PBIC), proposed steps that jurisdictions could take to plan, implement and sustain a bikeshare program. The guide surveyed and documented bikeshare business models, infrastructure considerations and funding options and shared specific performance metrics useful for monitoring and evaluating system success (*14*).

In the following year, the Institute for Transportation and Development Policy (ITDP) published a global evaluation of BSS to show how cities of different sizes, densities, and degrees of development had structured bikeshare systems. And while the document argues that there exists no single model for bikeshare implementation—rather cities must, ultimately, develop a system that is especially adapted to their own local context—it does identify key characteristics of more successful programs, including the provision of a dense station network, fully automated locking system, real-time monitoring of station occupancy rates and pricing structures that incentivize short trips (*4*).

A Mineta Transportation Institute report surveyed bikeshare operators, users and other stakeholders to better understand not only the status and characteristics of bikesharing operations in North America, but also the variety of impacts it was having on walking, bicycling and public transit. Study results were used to formulate a number of recommendations for enhancing bikeshare systems including improving the balance of stations between downtown and residential neighborhoods, building stronger partnerships between users, sponsors and local government and determining in advance the number of users and rides a system can support (*15*).

As bikeshare operational frameworks became more intricate, planning documents became more focused in their scope. For example, the National Association of City Transportation Official's (NACTO), Bike Share Siting Guide, emphasized the importance of site location planning in program success, highlighting best practices in station placement and design and how bikeshare stations can be leveraged to enhance walkability and broaden the reach of transit in urban settings (*16*).

SHIFT TOWARD EQUITY IN BIKESHARE PROGRAMMING

Early on in the development of bikeshare across the US, it became clear that system facilities were not adequately integrated into lower-income communities. Such criticisms mirrored transportation injustices—both past and present—that have burdened lower-income communities while simultaneously advantaging middle to higher-income neighborhoods (*17*, *18*).

Recent studies have shown that most investments in alternative transportation and active living plans and programs—including bikeshare—have largely benefitted middle- and upper-class communities despite the fact that low-income, Black, and Latino communities tend to experience: (1) lower rates of mobility/accessibility; (2) higher rates of obesity and related health risks; and (3) higher rates of pedestrian- and bicycle-related fatalities (*19*–*21*). Additionally, while diverse communities are embracing non-motorized transportation, advocates and planners became increasingly concerned that traditionally underserved populations were again being marginalized or unable to share in the full benefits of existing and future bicycle and pedestrian-oriented planning efforts.

These concerns led to a growing number of studies and advocacy efforts aimed at identifying and removing barriers to bikeshare in traditionally underserved areas. Recent research has found that the root causes of social inequality in bikeshare are multifold. First, communities of color often lack *geographic access* to bikeshare facilities due to a scarcity of stations and bikes being located there. One nationwide study of 35 large BSS programs found that more than three quarters (1,556 or 2,063 or 75.4 percent) of bikesharing stations across the US were located in communities with lower economic hardship whereas only 245 (or 11.9 percent) stations were located in communities with higher economic hardship (*22*).

Critics also pointed out that a lack of *functional access* to modern bikeshare systems may also constrain usage among lower-income groups, such as the use of credit-card based pricing and payment systems which restrict access to those without bank accounts (i.e., the "unbanked"). A series of reports by Portland State University, for example, concluded that high costs of membership, concerns about liability for the bicycle, incorrect knowledge about how to use bikeshare and a general lack of awareness of reduced-price memberships created a disproportionate number of barriers among lower-income respondents compared to their higher-income counterparts (*23*). More promising, however, is that the researchers found that bikeshare owners and operators have responded to these disparities by formally adopting equity into their planning processes. The study found that over half (57%) of US bikeshare systems now consider equity in their promotion, outreach, and marketing which is up from around 40 percent reported a few years ago (*8*). In recent years, cities have also taken steps to broaden bikeshare ridership among younger and older age groups, females and individuals with varying physical and cognitive abilities in addition to extending services to more suburban areas located outside the urban core.

II. DIVVY GROWTH AND EXPANSION

The Divvy bikeshare system, located in the City of Chicago and two adjacent suburbs, officially launched in June 2013 and—with over 11 million logged rides and 3 million trip hours through July 2017—it is one of the largest and most successful bikeshare systems in the country.

Similar to other large programs across the United States, most of the system's $18 million startup capital costs were acquired via the Congestion Mitigation and Air Quality (CMAQ) federal grant program, with the understanding that the bikeshare system would improve Chicago's transportation performance in multiple ways. Drawing from performance characteristics of similar systems implemented prior to Divvy (e.g., Montreal, Washington DC and New York), it was expected that Chicago's new bikeshare system would replace short automobile trips with bike trips, improve access to transit, and replace shorter transit trips, thereby simultaneously reducing private vehicle miles traveled and relieving pressure on congested roads and transit lines. The new bikeshare system also aligned with many of the regional transportation goals specified in the Chicago Metropolitan Agency for Planning (CMAP) GOTO 2040 plan (the Chicago region's metropolitan planning organization) which aimed to, among other objectives, increase cycling participation and better link "transit, housing and energy use through livable communities" (*24*).

The remainder of this section briefly characterizes three phases of Chicago's Divvy system beginning with its initial rollout in 2013 through its first and second expansions, in 2015 and 2016, respectively. Because Divvy is a docked system, we pay special attention to variations in the placement of bicycle stations over time as well as service and performance gaps across communities and sociodemographic groups.

To analyze Divvy's growth and expansion, we use both trip and station data that were made available via the Divvy website. The bikeshare data includes the date, time and frequency of trips as well as each trip's origin and destination station. Station data includes the geographic coordinates and capacity of Divvy docks as well as the date that each station was made operational. By merging the trips and stations datasets, we were able to create a comprehensive data table containing the origin (i.e., location of station where bike was rented), destination (i.e., location of station where bike was returned), date, duration and user type (i.e., subscriber vs. non-subscriber of customer) for each Divvy trip taken over a four-year period, June 2013 through June 2017 (N=11,544,688). A binary gender category (male or female) and birth year was also provided for 71.8 percent of the total trips, essentially those trips attributed to Divvy members.

In addition to the information provided by Divvy, each trip in the comprehensive table was attributed with additional contextual location information including the respective community area and study period or cohort associated with each origin and destination location and station. The three, distinct study periods (and respective date ranges) are organized with respect to the date when the specific station was made operational, namely: the *initial rollout* (6/1/2013-3/28/2015), *first expansion* (4/1/2015-6/30/2016) and *second expansion* (7/1/2016-6/30/2017). Figure 2 shows the cumulative trips and stations for each study period, whereas Figure 3 shows cumulative trips together with monthly Divvy trip totals taken between June 1, 2013 and June 30, 2017. Key characteristics of the geographic distributions and performances of Divvy stations collectively and for each study period are summarized below.

INITIAL ROLLOUT (JUNE 2013 – MARCH 2015)

Divvy officially began operation in June 2013 with the siting and activating of 100 stations: The first station was installed on June 10 and the first logged trip was initiated on June 27 of that year. The system quickly grew to 300 stations by October 2013 and, due in part to supplier issues, no additional stations were added to the system until April 2015. The initial set of bikeshare stations spanned across 21 of Chicago's 77 community areas, with the greatest station concentrations positioned in the Near West Side (41 stations), Near North (34), West Town (29) neighborhoods, the historic Loop (27) and adjacent communities to the north, west and south. Altogether the service area for the initial rollout (i.e., the non-overlapping area within ¼ mile of each station) was 31.5 square miles (Table 1).

Bikeshare site planning decisions for this initial period were carried out by the City of Chicago through a contracted engineering firm that helped guide the overall design of the system as well as the selection of specific station locations and dock installation. Station locations were informed by numerous types of information including a multi-factor suitability analysis which was used to estimate both the demand *potential* (informed by population density, employment density, share of population 20 to 39 years of age, percent of bike and walk commute share, business concentration, proximity to parks, public transit boardings and frequency) and locational *equity* (informed by household income, percent non-white population, educational attainment) of each location. Community-driven station location recommendations were also gathered via public meetings and an interactive website (*25*).

The initial station network was relatively dense, with stations positioned at an average quarter mile or approximately two city blocks from one another. According to the 2015 American Community Survey, population density within a ¼ mile of these stations is 20,761 people per square mile, which is considerably greater than the city as a whole (11,923 per square mile). The socio-demographics of residents within the service area of this initial cohort of stations is also predominantly white (mean of 57.8 percent) with lower rates of unemployment (mean of 5.1 percent of the labor force age 16 years or older) compared to service areas that benefitted from later expansions. And because most of the bikeshare stations are sited near Chicago's urban core—where public transit train and bus lines converge—they are readily accessible to transit customers, with the service area overlapping 84 CTA L and Metra stations and 2,549 CTA and Pace bus stops.

Figure 2. Cumulative Divvy Trips and Stations by Month and Study Period, June 2013-June 2017

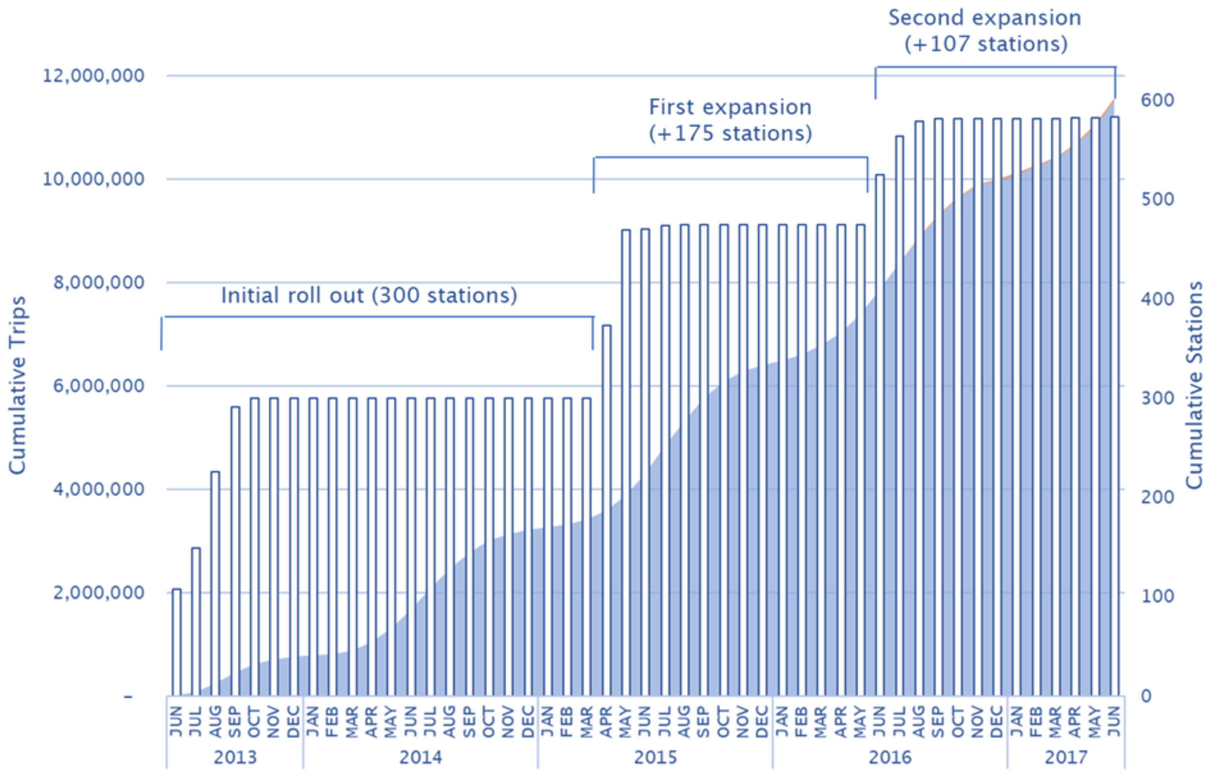


Figure 3. Cumulative and Total Divvy Trips by Month, June 2013-June 2017

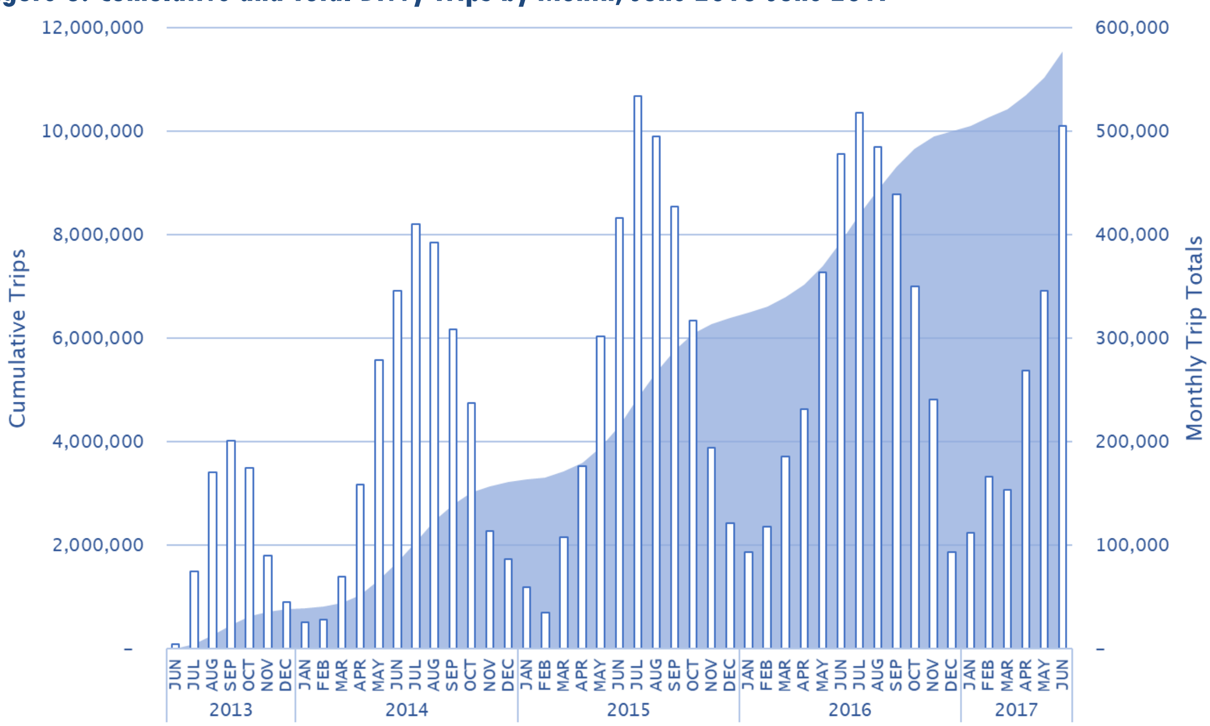


Table 1. Service Area Characteristics by Station Cohort

	Initial rollout	First expansion	Second expansion	*Total*[h]
Divvy stations	300	175	107	***582***
Service area (mi^2)[a]	31.5	30.6	19.2	***74.4***
Station density (mi^2)	9.52	5.72	5.57	***7.82***
Communities[b]	21	35	24	***47***
Population density (mi^2)	20,761	18,495	13,298	***17,671***
Station distance (mi)[c]	0.24	0.41	0.46	***0.33***
Train stations[d]	84	68	39	***191***
Bus stops[e]	2,549	2,260	1,377	***6,186***
% Non-white[f]	42.2	62.5	76.8	***57.8***
% Unemployed[g]	5.1	6.8	9.8	***9.3***

Notes: (a) Combined area of non-overlapping ¼ mile buffers from Divvy stations; (b) Number of communities that either intersect or are completely within service area; (c) Average minimum distance to closest Divvy station by service area; (d) Chicago Transit Authority (CTA) L train and Metra commuter train stops; (e) CTA and PACE suburban bus stops; (f) ACS, 2011-2015 5-year estimates, nonwhite and non-Latino; (g) ACS, 2011-2015 5-year estimates, population 16 years of age and older in the labor force; (h) attributes reported under *total* service area reflects data from all three station cohorts with no overlap (i.e., the present characteristics of the system service area at the time of this writing).

FIRST EXPANSION (APRIL 2015 to JUNE 2016)

In April 2015, as part of Divvy's first substantive expansion, 73 stations were added to the bikeshare network, with 102 more stations installed over the following four months. Nineteen communities—among them the Near North (additional 11 stations), Near West Side (8) and Loop (10)—added stations to their existing supply (a total of 93 or 53.1 percent of stations went into communities that already had stations) while the remaining 82 stations were distributed across sixteen new host communities scattered along the perimeter of the initial service area including the lower-income communities of Englewood (4), Humboldt Park (4) and North Lawndale (4).

The size of the first expansion station cohort service area is 30.6 square miles—similar in size to the initial rollout—although this first expansion service area has fewer bus stops and train stations due, in part, to the radial design of the region's train service which becomes increasingly dispersed outside the urban core. The first expansion cohort stations are also positioned further apart from one another compared to stations installed as part of the initial rollout (an average minimum distance of 0.41 miles versus 0.24 miles), thus the overall Divvy station network also became less concentrated during this period.

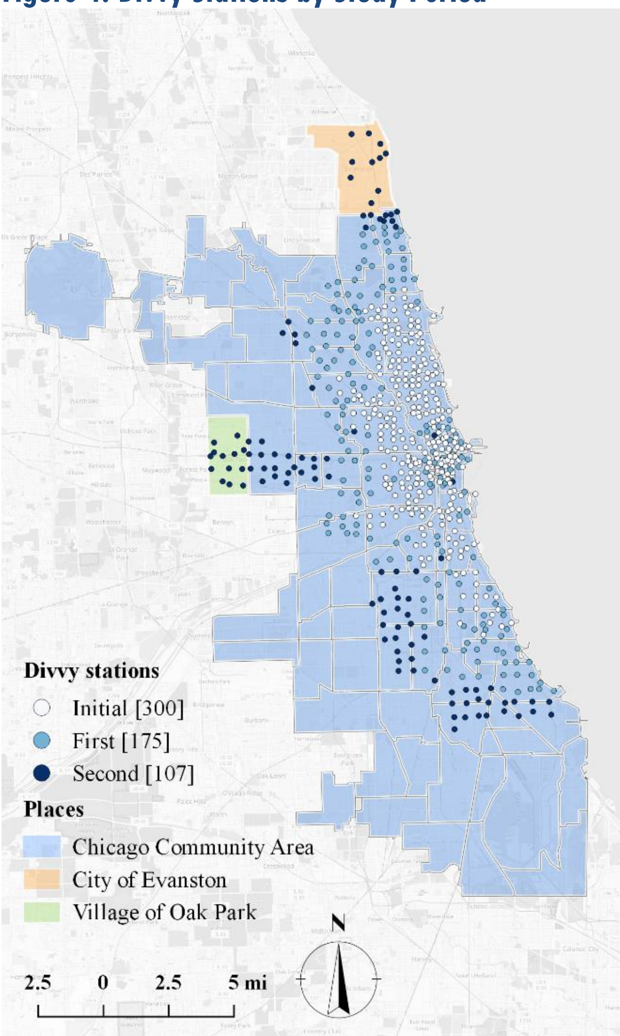
SECOND EXPANSION (JULY 2016 to JUNE 2017)

The second and latest expansion (at the time of this writing) commenced in June 2016 and included the addition of 107 stations to the Divvy network. The total service area (19.2 square miles), station density (5.57 stations per square mile), population density (13,298 per square mile) and transit proximity (1,377 bus stops and 39 train stations) for this second expansion were considerably less than past installations. Unlike previous expansions, nearly 60 percent of the stations installed over this period were sited in communities that, prior to this expansion, had no Divvy presence. Of these, over a third were located within lower-income communities, including Austin (14), West Englewood (6) and West Garfield Park (5). However, the stations installed during this second expansion were also more dispersed, with an average distance of 0.46 miles, double that of stations installed during the initial rollout.

Perhaps most unique to this period from a policy perspective, is that 23 new stations were added to the suburban communities of Oak Park and Evanston, which are adjacent to the western and northern boundaries of the city of Chicago, respectively. The expansion was made possible via a $3 million investment by the State of Illinois Department of Transportation (IDOT) distributed through its competitive and federally-funded Transportation

Enhancement Program (ITEP), which aims to provide funds for community-based projects that both expands travel choices for users and enhances the environmental aspects of transportation infrastructure. As part of the grant distribution process, inter-agency agreements were arranged between Chicago and the suburban communities, each of which paid 20 percent of the total grant amount received; $120,000 in local match by Oak Park and $80,000 by Evanston.

Figure 4. Divvy Stations by Study Period



While the inter-agency agreements included rigid requirements with respect to several aspects of the system including advertising, pricing, revenue-sharing and operation, the process for siting bikeshare stations was carried out independently by each suburb. The Village of Oak Park, for example, contracted with a regional nonprofit transportation advocacy group to develop a bicycle and bike share feasibility plan that also included guidance for the station site selection process (Village of Oak Park 2015). The station siting methodology for Oak Park resembled the strategy carried out by the City of Chicago for its initial rollout of Divvy. That is, the study utilized responses to community surveys as well as results from a demand model that weighted a variety of variables, such as population density, employment density, rail transit stations, and other demographic characteristics to determine optimal conditions within the village to locate bikeshare stations. The bikeshare feasibility study identified 13 sites for placing the first phase of implementation, to be placed in areas that received both higher bike share scores and locations that contributed to a denser network within the system coverage area.

In contrast, the City of Evanston used information from a wide variety of information sources—e.g., including Northwestern University students' capstone projects, online survey data collected as part of the city's bike plan update, and other factors such as proximity to transit, access to retail spaces, proximity to retail spaces, popular public venues, major employers and population density—to evaluate options for locating the initial eight bike share stations. Both suburbs largely assumed that their initial community-specific rollouts of Divvy stations would be just one of several future expansions.

SERVICE AND PERFORMANCE GAPS

Surely the Divvy system has greatly increased mobility through bicycle access among both Chicago's residents as well as short-term visitors and tourists. Despite these gains in geographic access, however, over forty percent of the city's community areas (i.e., 32 of the 77) still do not, at the time of this writing, host a Divvy station. And, for those communities that do have Divvy bicycles within their boundaries, functional access to the system and system usage—such as the average number of trips per station—can vary greatly, as mentioned above. This section explores variations in both geographic access and system usage across the study area and within the

Divvy network.

The comprehensive Divvy dataset discussed up to this point represents trips taken over a four-year period beginning June 2013 through June 2017. However, to compare usage across stations, we consider only the 3,677,088 trips taken over the approximately one-year period, 6/1/2016 through 6/31/2017, when all 582 present stations were active. Performance characteristics for this period (Table 2) indicate major differences in Divvy system utilization (in terms of trips and trip times) across the three station cohorts. Most notable is that the average number of trips per station is considerably greater for stations installed during the initial rollout (10,161) compared to stations activated later in the first and second expansions (3,285; and 503 trips per station, respectively).

In 2013, soon after the initial outlay of stations in Chicago, criticisms arose concerning the lack of Divvy bikesharing stations in communities on the South and West sides of the city. Figure 4 shows that over two-thirds of the 300 stations installed between June and October 2013 were concentrated in six communities in the north and central areas of the city, led by the Near West Side (41), Lincoln Park (36), Lake View (34), Near North Side (34), West Town (29) and the Loop (27).

We developed an economic hardship index to further examine both the distribution and utilization or performance of stations across neighborhoods. The index is composed of six variables drawn from the 2015 American Community Survey 5-year estimates, namely: percent overcrowded; percent unemployed; percent with less than high school diploma; percent dependent population; percent spending more than 30 percent of income on housing; and percent with no health insurance. The six variables were gathered at the census block group level before aggregating to

Table 2. Performance Characteristics by Station Cohort (Trips taken between June 2016 to July 2017)

	Initial rollout	First expansion	Second expansion	Total
Stations	300	175	107	582
Divvy trips (000s)	3,048.4	574.9	53.8	3,677.1
% of Divvy trips	82.9%	15.6%	1.5%	100.0%
Average trips per station	10,161	3,285	503	6,318
Trip hours (000s)	817.4	166.9	16.2	1,000
Minutes per trip	16.1	17.4	18.1	16.3
Male to Female	3.0	2.9	2.9	3.0

Figure 5. Proportion of Divvy Stations by Economic Hardship Category and Study Period

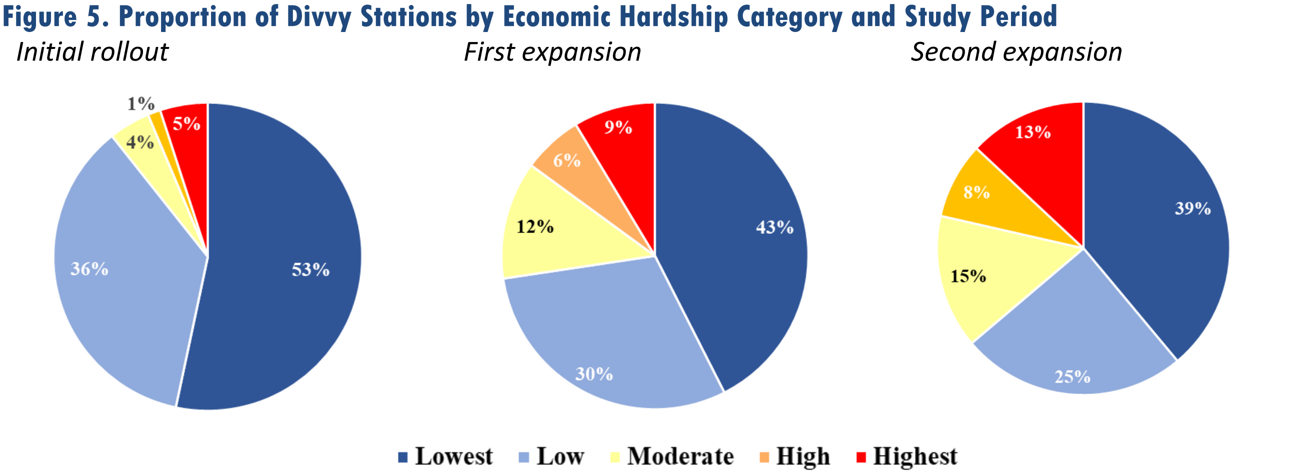


Table 3. Number, Percent and Performance of Stations by Station Cohort and Economic Hardship Category (Trips taken between June 2016 and July 2017)

	Initial rollout		First expansion		Second expansion	
	Stations (%)	*Trips [000s] (%)*	*Stations (%)*	*Trips [000s] (%)*	*Stations (%)*	*Trips [000s] (%)*
Lowest	160 (27.5%)	2,089 (56.8%)	42 (7.2%)	376 (10.2%)	24 (4.1%)	35 (1%)
Low	108 (18.6%)	901 (24.5%)	35 (6%)	124 (3.4%)	2 (0.3%)	1 (0%)
Moderate	13 (2.2%)	16 (0.4%)	46 (7.9%)	51 (1.4%)	27 (4.6%)	12 (0.3%)
High	4 (0.7%)	9 (0.2%)	26 (4.5%)	14 (0.4%)	19 (3.3%)	4 (0.1%)
Highest	15 (2.6%)	32 (0.9%)	26 (4.5%)	9 (0.3%)	35 (6%)	2 (0.1%)
Total	***300 (51.5%)***	***3,048 (82.9%)***	***175 (30.1%)***	***575 (15.6%)***	***107 (18.4%)***	***54 (1.5%)***

Figure 6. Distribution of Divvy Stations by Study Period and Neighborhood Area

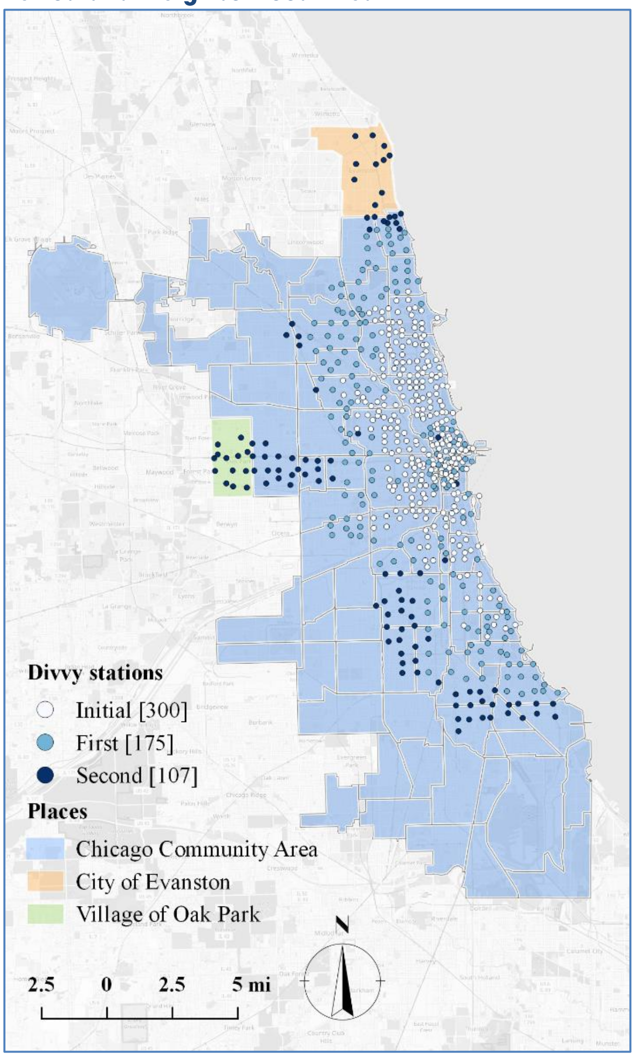
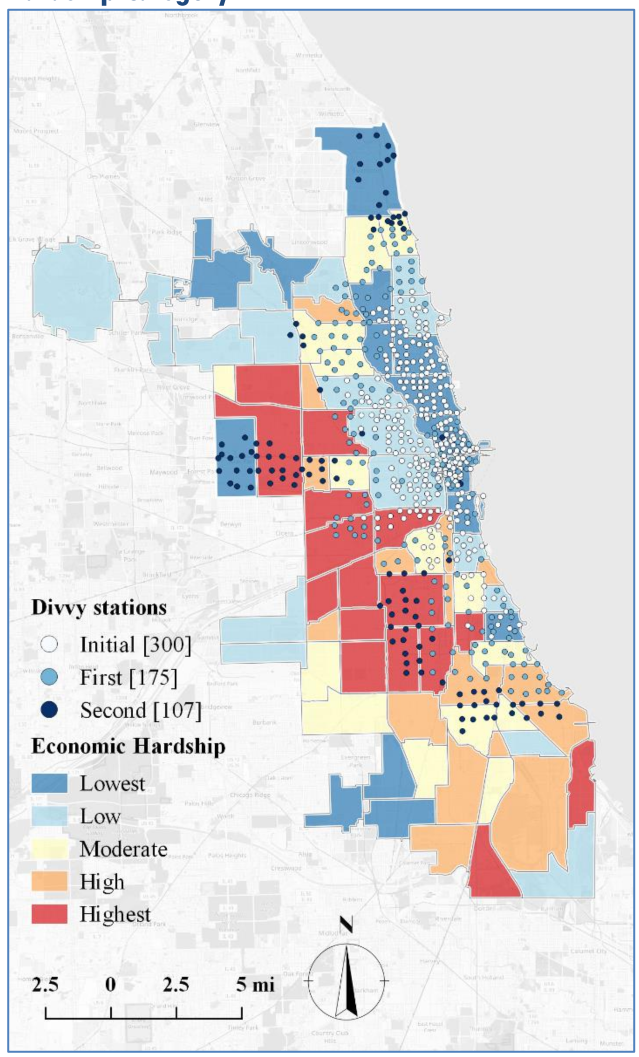


Figure 7. Distribution of Divvy Stations by Economic Hardship Category



community areas using a spatial areal weighting procedure. Each of the community area-level variables were then independently ranked by Z score value and combined via an additive procedure to create the index. Finally, the index values were then categorized into quintiles representing varying levels of economic hardship, with the "highest" index category indicating worse economic conditions. Figure 5 maps the number of distribution of Divvy stations by economic hardship category, clearly showing disproportionate concentrations of stations within community areas with relatively low levels of hardship, although the distributions have trended toward becoming more equitable over time.

Table 4 shows not only that Divvy system utilization is considerably lower for stations activated in the first and second expansions, as stated earlier, but that the productivity of stations is also lower in communities with greater economic hardship. For example, the 21.5 percent of total Divvy stations located within communities with higher economic hardship produced only 1.9 percent of logged trips within the study period (i.e., June 2016 and July 2017). The lowest rates of Divvy usage were among stations installed during the second expansion within communities with higher economic hardship.

In addition to performance disparities across economic hardship categories, this study also found considerable usage gaps by gender across Chicago community areas and nearby suburbs. Many of the places outside the urban core, including the suburbs of Evanston (3.33) and Oak Park (4.14) reported larger gender gaps in system usage–i.e., where the ratio of Divvy trips taken by male riders exceeded the number of trips taken by female riders—over the study period relative to communities on Chicago's north side such as Rogers Park (2.14), Lincoln Park (2.19) and Uptown (2.31). Figure 8 below also indicates that the gender gap is seasonal in that it grows widest in the winter months, narrows in the spring and summer before rising again when temperatures drop in the fall. Over the past four years, however, the gender gap has begun to close system wide—dropping from an annual average of 3.5 in 2013 to 3.1 in 2017—in part due to notable gains in female ridership in cooler months over time.

Figure 4. Male to Female Trips Ratios for Select Places (Trips taken between June 2013 and July 2017)

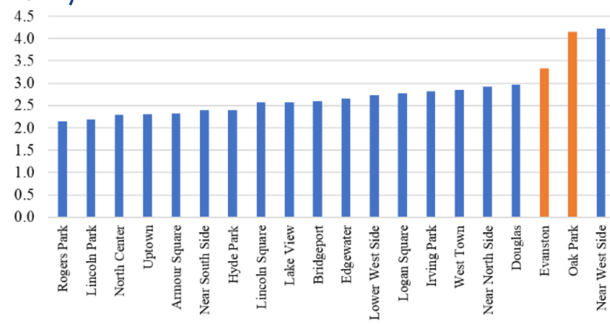
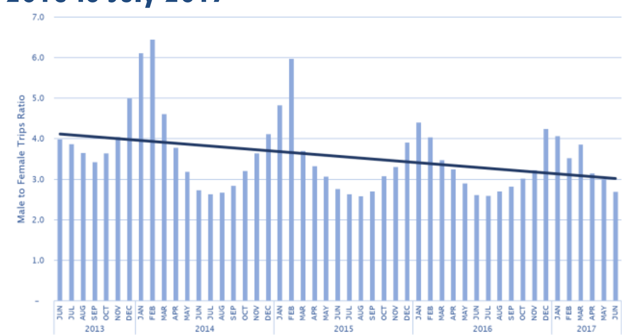


Figure 5. Monthly Male to Female Trips Ratios, June 2013 to July 2017



III. WHAT DRIVES DIVVY RIDERSHIP?

In this section we develop a series of statistical models designed to explain variability in Divvy system usage at the station level. This process began with an extensive review of academic literature, BSS websites and other professional reports that could be used to inform the selection of response and predictor variables as well as relevant data sources and methods.

Past bikeshare studies can be crudely categorized into four types: (1) *descriptive studies* that inventory and report the characteristics of existing systems such as their respective locations (typically at the city-scale), sizes (i.e., number of bicycles and docks) and business models (Shaheen et al. 2014; TDG and PBIC 2012); (2) *operations-related analyses* which examine and, at times, offer solutions to widespread funding, public safety and/or logistics challenges (e.g., balancing supply and demand across stations, ensuring fiscal sustainability, accommodating and improving helmet use) posed by BSS (Fishman, Washington, and Haworth 2013; Friedman et al. 2015; Kraemer, Roffenbender, and Anderko 2012; Rainer-Harbach et al. 2013; Siavash Shahsavaripour 2015); (3) explorations into the *factors that influence bikeshare utilization* (Faghih-Imani et al. 2014, 2014; Fishman 2015) that explore determinants of ridership patterns and flows; and (4) *transportation system impacts* which examine the impacts (e.g., mode shifts, public health and environmental improvements) that BSS has on the functioning of the broader transportation system and society, more generally (Martin and Shaheen 2014). For this analysis, we largely draw from findings that fall into the third category of studies, those concerned with bikeshare utilization or what drives ridership throughout and between bikeshare programs although the data, analytics and results reported below may have broader implications that speak to other research domains.

MODEL DATA AND ANALYTICAL PROCEDURES

The model data and analytical procedures used in this study follow a multi-step process that includes determination of a study period, factor determination, variable operationalization and model specification. Each of these steps is discussed briefly below beginning with the determination of an appropriate study period.

For the statistical analyses presented below we use the subset of trips taken over the study period when all 582 stations were operational; i.e., the 3,677,088 trips taken between 6/1/2016 and 6/31/2017. This period was deemed appropriate to employ in the statistical models for two reasons. First, it can rationally be assumed that, throughout this period, system users were given equal opportunity to ride to and from all stations throughout the Divvy network. Second, by aggregating trips over an entire year—as opposed to weeks or months which is common in past studies—the analyses minimize the effects of seasonal variations on bikeshare usage and season-sensitive relationships between response and predictor variables, more generally.

Building on past studies, the present analysis aims to better understand variability in station use not only with regard to bikeshare *trip generation* but also *trip destination*. Recent academic studies (and bikeshare operators themselves) have found that bicycle facilities (e.g., bike lanes, paths and related treatments), bikeshare station capacity, land use and built environment factors can have differential impacts on station departure versus arrival rates (Faghih-Imani et al. 2014; Faghih-Imani and Eluru 2015). The dependent variables for this study, then, represent total rentals (by origin location), returns (by destination location) and flows (rentals plus returns) over the study period. Log transformations of the three variables were computed in order to adjust for the skewed distributions of station activity by higher station values. The log-transformed variables were then used as response variables in the statistical analyses.

We identified and employed 32 theoretically-grounded factors for explaining variability in bikeshare usage. These factors can be organized into five categories: (1) *neighborhood design* or characteristics of the built environment including road networks and housing; (2) *accessibility* or spatio-temporal relationships between geographic features such as the proximity to and distributions of BSS stations, transit stops and jobs; (3) *socioeconomic* or demographic variables relating to population composition and economic performance; (4) *travel behavior* including auto ownership and commuting patterns of workers; and (5) *bikeshare network-specific factors* which relate to bikeshare station capacity (e.g., number of station docks) and characteristics of Divvy riders (e.g., male, female).

The operationalization of the above factors into suitable variables for regression analysis often required further segmentation and/or processing. For example, in order to account for both site- and neighborhood-level influences, factors were aggregated at both the station (i.e., summary of characteristics within ¼ mile of each Divvy station) and community (i.e., summary of values at each station's host community area or municipality) scales. Further, in order to reduce aggregation biases resulting from using a single areal unit of analysis, accessibility factors were summarized at multiple distances from each station and, in some cases, further segmented by type. The rather broad factor of *public transit*, for example, was subdivided into 14 unique variables that measure different aspects of the area's public transit system and their geographical relationships with bikeshare stations. These more nuance measurements take into account transit type (e.g., bus, city rail and commuter rail), scale of aggregation (e.g., transit characteristics within ½- and 1-mile of a bikeshare station) and summary levels (i.e., counts of stops/stations versus nearest closest stop/station per spatial level of aggregation).

Summarizing variable data at the station buffer and community scales was less complicated when source data were represented as discrete points (e.g., points of interest and street intersections). In other cases when source data were summarized as regions or polygons (e.g., land use, LODES data by census block and ACS data by census block group), areal weighting procedures were used to allocate variable counts proportional to the area of overlap of the target community area or station buffer geography. In some cases, data were only provided at coarser, community-level geographies such as the housing composition, foreclosure and sales data made available by DePaul University's Institute of Housing Studies.

Altogether, over 100 unique independent variables were developed and employed in the statistical analyses (Table 6). While most of the variables employed in this research largely replicated those in previous studies, others are less commonly used to explain variability in bikeshare activity. Measures of public transit job accessibility, walkability, economic hardship and ethnic/racial diversity, for example, were computed because they have shown to be important predictors of other urban phenomena (e.g., spatial mismatch, non-motorized trip generation, quality of life). Such indices were employed in the regression analyses in order to test their correlations with bikeshare system performance.

Including such a large number of estimators in the statistical analyses was thought to be necessary in order to identify the strongest and most significant predictors of bikeshare activity across unique factor groups (e.g., socioeconomic, accessibility, urban design) while simultaneously avoiding biases associated with omitting relevant variables. However, over specifying the models with an abundance of independent variables—some of which may be collinear and redundant—can lead to other specification problems including inflated standard errors, sign ambiguity among the regression coefficients and lower predictive power for the models as a whole.

In order to address these limitations, a multivariate adaptive regression splining (MARS) technique was used to fit each of the three dependent variables to the same set of predictor variables. MARS models can be seen as extensions of linear regressions but, unlike ordinary least squares regression models, are non-parametric and are able to automatically control for model heteroskedasticity and nonlinear relationships between response and predictor variables. Further, MARS "prunes" the number of estimators in the regression model by evaluating the relative strength and predictive efficiency of variable subsets over several iterations. The output model resolves with a subset of the strongest predictors among all input variables.

Estimates of variable importance in each MARS model was carried out using three criteria: (1) the *number of subsets* for which each variable is included in model runs, or the number of times each variable is included in a relatively efficient model run; (2) the residual sum of squares or *RSS criterion* which calculates the decrease in the RSS for each subset of variables relative to the previous subset, with variables that cause larger net decreases in RSS considered more important. Note that, for ease of interpretation, the summed decreases are scaled so the largest summed decrease is 100. Lastly (3) the generalized cross-validation (GCV) criterion is essentially the RSS penalized by the effective number of model parameters in each subset. This variable selection process, therefore, yields a pruned MARS model composed of variables weighted by their relative importance. All statistical analytical procedures—MARS and estimates of variable

Table 6. Model Variables, Definitions and Data Sources

	Description	Data source
Dependent variables		
ln(trips_from)	Annual Divvy trips by rental (origin) station	Divvy
ln(trips_to)	Annual Divvy trips by return (destination) station	Divvy
ln(trips_flow)	Annual Divvy rentals + returns (flow) by station	Divvy
Independent factors/variables		
Neighborhood design		
streets	Street network density (network miles per mi^2)	TIGER/Line, US Census[a]
bike facilities	Bike facilities density (network miles per mi^2)	Multiple sources[b]
intersections	Intersection density (intersections per mi^2)	TIGER/Line, US Census
land use	Land use diversity (0 [lowest] – 1 [highest])	Adapted from CMAP[c]
walkability	Total walkability index (0 [lowest] – 1 [highest])	Adapted from CMAP
population density	Total population (per mi^2)	ACS 2015, 5-Year[d]
housing density	Housing unit density (units per mi^2)	ACS 2015, 5-Year
% multi-family	Percent multi-family (5 or more) units	ACS 2015, 5-Year
% condo units	Percent of housing units, condo	DePaul IHS[e]
% built < 1950	Percent of housing units built prior to 1950	ACS 2015, 5-Year
Accessibility		
distance to CBD	Distance from Divvy station to Chicago city hall	Adapted from Divvy
job accessibility	Accessibility to jobs via public transit	Multiple sources[f]
retail jobs	Retail job density (per mi^2)	LODES, 2015[g]
higher-income jobs	Jobs with earnings > $3,333 per month (per mi^2)	LODES, 2015
public transit	Number of and distance to stations/stops by type	RTAMS[h]
points of interest	Points of interest density (locations per mi^2)	Open Street Map
Divvy stations	Proximity to Divvy stations	Adapted from Divvy
Socioeconomic		
% dependent population	Percent of population <18 or >=65 years of age	ACS 2015, 5-Year
% nonwhite population	Percent of total population non-White, not Latino	ACS 2015, 5-Year
racial/ethnic diversity	Race and ethnicity diversity	ACS 2015, 5-Year
economic hardship	Economic hardship index (0 [lowest] - 1 [highest])	ACS 2015, 5-Year
foreclosure rate	Residential foreclosures per 100 parcels	DePaul IHS
house sales	Residential house sales per capita	DePaul IHS
crime density	Violent crimes (per mi^2)	Multiple sources[i]
Travel behavior		
% own vehicle	Percent of households that own private vehicle	ACS 2015, 5-Year
% drive alone to work	Percent of workers who drive alone to work	ACS 2015, 5-Year
% bike to work	Percent of workers who commute by bicycle	ACS 2015, 5-Year
% walk to work	Percent of workers who commute by walking	ACS 2015, 5-Year
Divvy-specific factors		
station capacity	Number of docks at Divvy bikesharestation	
% female trips	Percent of Divvy trips by female riders	Adapted from Divvy
male to female trip ratio	Male to female Divvy trips ratio	Adapted from Divvy
% subscriber/member trips	Percent of Divvy trips by program subscribers	Adapted from Divvy
% trips during peak periods	Percent of Divvy trips during peak AM, PM periods	Adapted from Divvy
diurnal trip index	Diurnal Divvy trips diversity index	Adapted from Divvy

Notes: (a) Topologically Integrated Geographic , US Census Bureau; (b) City of Chicago; Village of Oak Park; City of Evanston; (c) Chicago Metropolitan Agency for Planning; (d) American Community Survey 2011-2015, 5-year estimates; (e) DePaul Institute of Housing Studies; (f) LODES, ACS, RTAMS, OpenStreetMap; (g) Longitudinal Origin-Destination Employment Statistics, US Census Bureau; (h) Regional Transit Authority Mapping Statistics; (i) City of Chicago; Village of Oak Park; City of Evanston

Table 7. Summary Statistics and Bivariate Correlation Coefficients for Select Model Variables

Description	Variable Name	Mean	SD	*from* Corr	*to* Corr	*flow* Corr
Dependent Variables						
Annual Divvy trips by rental (origin) station	*s_trips_from*	*6,307*	*8,736*	*1.000*	*0.995*	*0.999*
Annual Divvy trips by return (destination) station	*s_trips_to*	*6,307*	*8,880*	*0.995*	*1.000*	*0.999*
Annual Divvy rentals + returns (flow) by station	*s_trips_flow*	*12,614*	*17,596*	*0.999*	*0.999*	*1.00*
Independent variables						
Neighborhood Design						
Bike facilities density (network miles per mi2)	**s_bikelanedensity**	**3.19**	**2.50**	**0.40**	**0.39**	**0.39**
Bike facilities density (network miles per mi2)	**c_bikelanedensity**	**2.89**	**1.37**	**0.55**	**0.53**	**0.54**
Percent of housing units, condo	**c_pctcondores**	**31.51**	**23.92**	**0.62**	**0.61**	**0.62**
Percent multi-family (5 or more) units	**s_pctmultihu**	**55.27**	**29.21**	**0.57**	**0.56**	**0.56**
Accessibility						
Divvy stations within 1-mile radius	**s_div1mi**	**22.95**	**17.69**	**0.64**	**0.62**	**0.63**
Divvy stations within 1/2 mile radius	**s_divhalfmi**	**5.97**	**5.96**	**0.61**	**0.58**	**0.60**
Points of interest density (locations per mi²)	**s_poisdens**	**101.31**	**84.69**	**0.57**	**0.55**	**0.56**
Points of interest density (locations per mi²)	**c_poisdens**	**465.92**	**491.50**	**0.55**	**0.53**	**0.54**
CTA L stations within 1 mile	**s_L1mi**	**5.45**	**5.79**	**0.56**	**0.53**	**0.55**
Accessibility to jobs via public transit	**s_jobaccess**	**936,740**	**193,736**	**0.48**	**0.47**	**0.47**
Average distance to Divvy stations	**s_avgdist2div**	**6.18**	**1.84**	**-0.45**	**-0.44**	**-0.44**
Average min distance to Divvy stations	**c_avgmin2div**	**0.31**	**0.12**	**-0.57**	**-0.56**	**-0.57**
Socioeconomic						
Percent of workers earning >= $3,333/mo	**s_rac_pcthigh**	**51.51**	**19.61**	**0.56**	**0.54**	**0.55**
Percent unemployed	**s_pctunemp**	**6.85**	**4.35**	**-0.40**	**-0.40**	**-0.40**
Residential foreclosures per 100 parcels	**c_allresper100**	**0.66**	**0.62**	**-0.42**	**-0.42**	**-0.42**
Economic hardship index (0 [low] - 1 [high])	**s_ehindex**	**0.69**	**0.38**	**-0.48**	**-0.47**	**-0.47**
Percent of population non-White, not Latino	**s_pctpopnonwht**	**56.16**	**28.26**	**-0.51**	**-0.50**	**-0.50**
Percent dependent population (<18 or >=65)	**c_pctdeppop**	**13.37**	**3.74**	**-0.57**	**-0.55**	**-0.56**
Percent of workers employed in retail sector	**s_rac_pctretail**	**7.88**	**2.97**	**-0.59**	**-0.58**	**-0.59**
Travel behavior						
Percent commute to work by walking	**s_pctcomwalk**	**12.69**	**15.13**	**0.57**	**0.55**	**0.56**
Percent commute to work by walking	**c_pctcomwalk**	**11.67**	**11.33**	**0.51**	**0.49**	**0.50**
Percent of commuters who drove alone	**c_pctcomdral**	**40.76**	**10.15**	**-0.56**	**-0.54**	**-0.55**
Percent of commuters who drove alone	**s_pctcomdral**	**39.94**	**12.72**	**-0.58**	**-0.57**	**-0.58**
Divvy-specific factors						
Diurnal Divvy ridership diversity index	**s_divtrips_nd**	**79.70**	**5.56**	**0.28**	**0.27**	**0.28**
Male to female Divvy trip ratio	s_mal2femtrips	3.26	2.59	-0.01	-0.02	-0.02

Total observations (N) = 582; Bivariate correlations in bold are significant at the p<0.1 level.

importance—were carried out using RStudio version 1.1.183 statistical program together with the `evimp` package.

Descriptive statistics and bivariate correlations between highly correlated explanatory variables (i.e., statistically significant correlations with absolute values of 0.4 or greater) and each of the three response variables are shown in Table 7. The correlations suggest that several explanatory variables have strong and significant correlations with Divvy usage across each of the five variable categories. Further, the dependent variables themselves have strong positive linear relationships

Table 8. Variable Selection Results by MARS Model

Variable	Highest Rank	ln(trips_from)			ln(trips_to)			ln(trips_flow)		
		Subsets	GCV	RSS	Subsets	GCV	RSS	Subsets	GCV	RSS
c_allresper100	*15*	15	100	100	14	100	100	14	100	100
s_pctpopnonwht	*14*	14	56.08	56.54	-	-	-	-	-	-
s_pctmultihu	*13*	13	42.89	43.53	9	33.23	33.84	9	33.30	33.88
c_pctcondores	*12*	11	24.30	25.57	12	49.46	49.93	12	49.46	49.92
s_jobaccess	*12*	12	31.54	32.51	11	35.09	35.76	11	35.13	35.78
s_pctcomdral	*11*	7	12.24	13.95	11	35.09	35.76	11	35.13	35.78
s_ehindex	*9*	-	-	-	9	23.84	24.76	9	23.67	24.58
s_divtrips_nd	*9*	9	16.06	17.74	6	13.75	14.95	6	13.43	14.65
s_mal2femtrips	*8*	8	14.05	15.75	7	16.74	17.84	7	16.55	17.65
s_pctunemp	*6*	6	10.08	11.86	-	-	-	-	-	-
c_pctcomwalk	*5*	-	-	-	5	11.21	12.47	4	9.53	10.68
s_avgdist2div	*4*	4	6.58	8.40	4	9.63	10.79	3	8.10	9.10

suggesting substantial correspondence across stations with respect to rental and return activity. All of the highly correlated explanatory variables have the expected signs or theoretical directional relationships with the response variables.

REGRESSION MODEL RESULTS

Initial MARS results show that variables across each of the five categories are represented in the pruned model specifications, suggesting that neighborhood design, accessibility, socioeconomic and related bikeshare characteristics all have considerable predictive power in explaining variability in bikeshare activity. Rates of foreclosure properties, multifamily housing units and condominium units, job accessibility and drive alone commute mode share were among the five most efficient predictors across all three models (Table 8). Percentage of the population nonwhite and unemployed were stronger predictors for explaining variability in trip generation (i.e., Divvy rental activity) whereas economic hardship and percent walk commute mode share were more strongly correlated with trip destination and flow activity. Further, station-level (or 1/4 mile distance from station) variables were also selected more frequently by the MARS model than the variables aggregated at the community or place-level (i.e., community areas for stations in Chicago or the municipal level for Evanston and Oak Park), suggesting that bikeshare activity may be driven more by localized patterns than broader, community characteristics.

Various diagnostic characteristics of the MARS models are presented in Figure 6. The residuals versus fitted graphs (upper section of Figure 6) show that the residuals exhibit constant variance across the low and high fitted values, suggesting minimal presence of heteroscedasticity within all three models. Model selection charts (middle section of Figure 7) shows the cross-validation statistics for the iterative or variable subsets for each MARS model. The vertical black dotted line shows the optimal number of terms (i.e., variables) determined whereas the pale pink lines show the R-squares for each of the model runs or “folds”. The cumulative distribution charts (bottom section of Figure 7) shows the cumulative distributions of the absolute values of the residuals for each model. In all models, the graph quickly rises to 1 indicating the high explanatory power of each term. For all models, the 95 percent of the absolute value of residuals are within 3.0 units of the observed value.

As discussed earlier, MARS controls for nonlinearity in relationships between response and predictor variables. Figure 8 shows that many of the explanatory variables do indeed exhibit nonlinear relationships that *hinge* at distinct thresholds. For example, when the percentage nonwhite grows to 92 percent, bikeshare activity drops at a faster rate with each unit increase in the predictor. In contrast, the effect of multifamily units on bikeshare activity is minimal until a threshold value of 20 percent is reached and the positive relationship between proportion multifamily and system usage becomes stronger. Further investigation of these hinges or tipping points for each factor may yield useful information for understanding and planning for bikeshare programs.

Table 9 shows coefficient estimates (both unstandardized and standardized) for linearized variables selected as part of the MARS model runs. The coefficients can be used to interpret the potential impact of each predictor on each of the three types of bikeshare activity. Coefficients must first be adjusted to account for the log-transformed dependent variable. Standardized coefficients were ordered from highest value to lowest value such that the strongest predictors are on either end (depending on whether the variable has a proportional or inverse relationship with the dependent variable) of the ordered list by model. Based on this ordering, percentage of multi-housing units (0.26) and job accessibility (0.18) were the strongest, positively correlated predictors of trip generation. For example, a one percent increase in the share of multifamily

Figure 8. MARS Diagnostics and Results by Model

ln(trips_from) ***ln(trips_to)*** ***ln(trips_flow)***

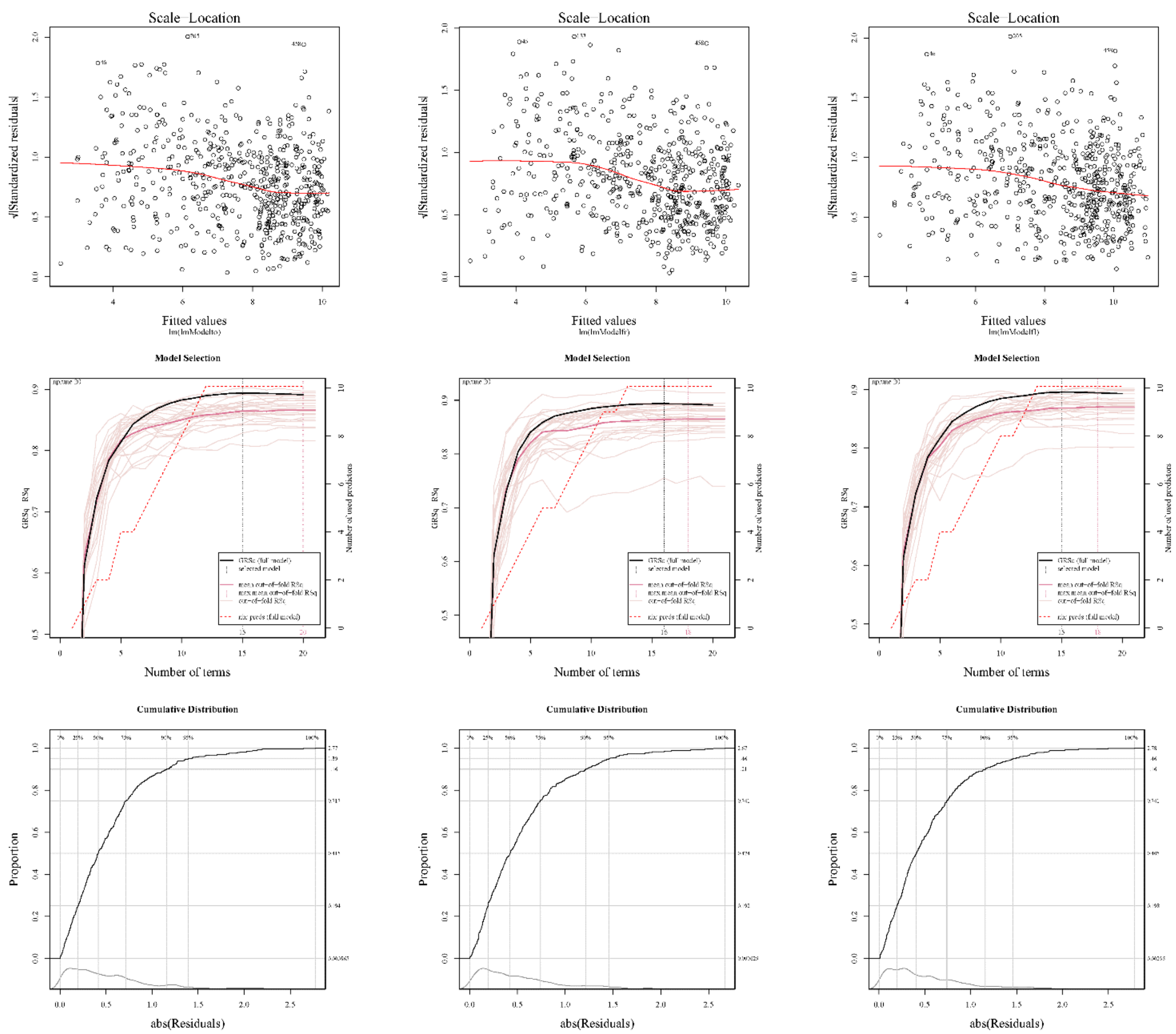


Figure 9. MARS Prediction Intervals for Select Explanatory Variables

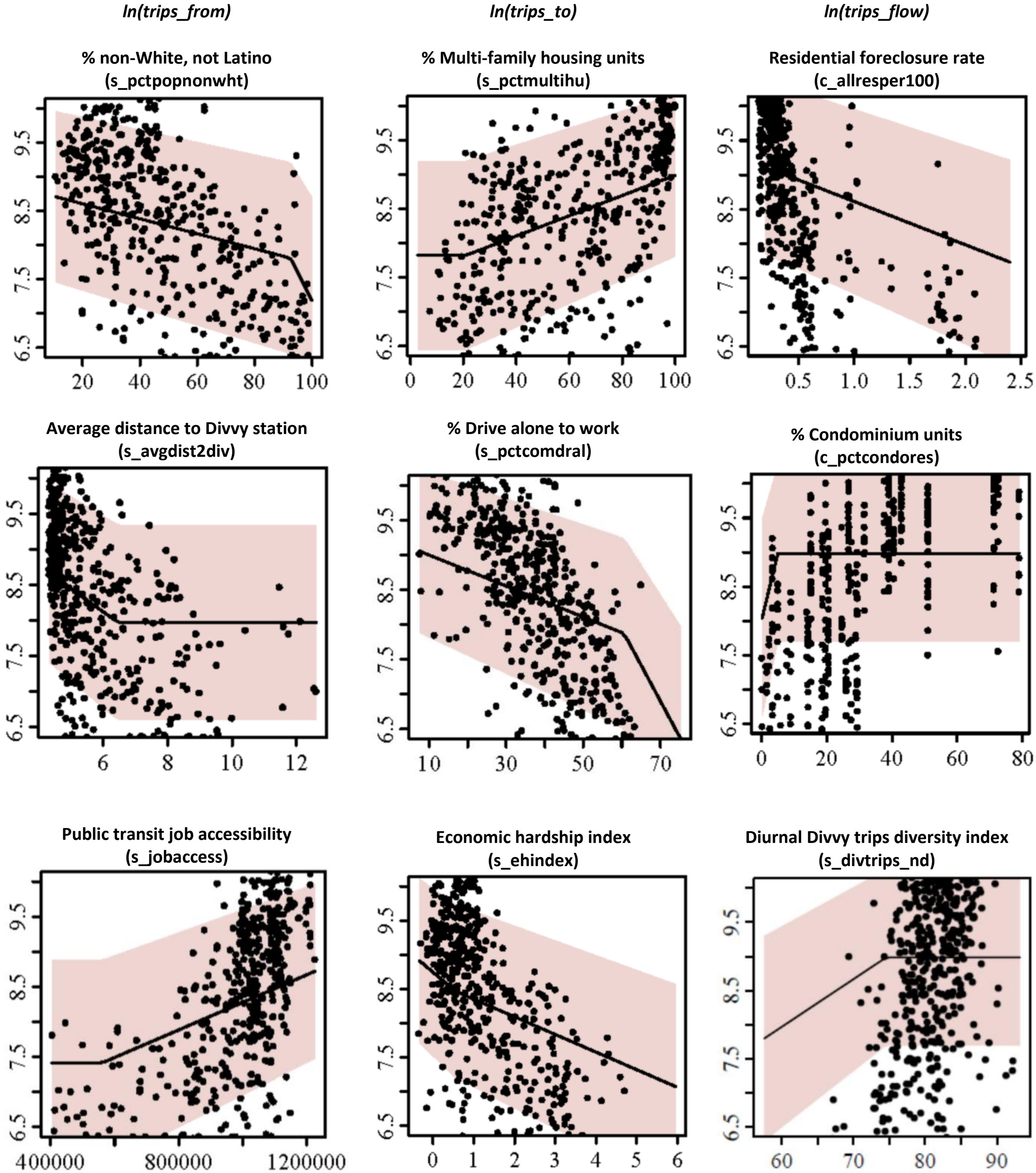


Table 9. Linear Regression Results for Three Divvy Usage Models (from, to, flow)

Variable	Standardized	Coefficient	Std. Error	t value	Pr(>|t|)
ln(trips_from)					
(Intercept)	**0.00**	**5.55**	**0.72**	**7.68**	**0.00**
s_pctmultihu	**0.26**	**0.02**	**1.79E-03**	**9.92**	**0.00**
s_jobaccess	**0.18**	**1.84E-06**	**3.11E-07**	**5.92**	**0.00**
s_divtrips_nd	**0.08**	**0.03**	**0.01**	**4.27**	**0.00**
s_bikelanedensity	**0.03**	**0.03**	**0.01**	**1.96**	**0.05**
s_avgdist2div	**-0.09**	**-0.10**	**0.03**	**-2.94**	**0.00**
s_pctcomdral	**-0.09**	**-0.01**	**3.45E-03**	**-4.23**	**0.00**
s_pctunemp	**-0.15**	**-0.07**	**0.01**	**-6.32**	**0.00**
s_pctpopnonwht	**-0.18**	**-0.01**	**1.92E-03**	**-6.57**	**0.00**
c_allresper100	**-0.22**	**-0.70**	**0.09**	**-7.62**	**0.00**
s_mal2femtrips					0.54
c_pctcondores					0.92

Above model: R-squared: 0.87; Adj r-squared: 0.86; F-statistic: 337.907 on 11 and 570 DF, p-value: 0.000
(Full model: R-squared: 0.93; Adjusted R-squared: 0.92; F-statistic: 66.978 on 100 and 482 DF, p-value: 0.000)

Variable	Standardized	Coef	Std. Error	t value	Pr(>|t|)
ln(trips_to)					
(Intercept)	**0.00**	**5.80**	**0.71**	**8.13**	**0.00**
s_pctmultihu	**0.26**	**0.02**	**1.76E-03**	**10.02**	**0.00**
s_jobaccess	**0.16**	**1.66E-06**	**3.08E-07**	**5.39**	**0.00**
s_divtrips_nd	**0.08**	**0.03**	**0.01**	**4.50**	**0.00**
s_bikelanedensity	**0.04**	**0.03**	**0.01**	**2.56**	**0.01**
c_pctcomwalk	**-0.11**	**-0.02**	**4.46E-03**	**-4.30**	**0.00**
s_avgdist2div	**-0.12**	**-0.13**	**0.03**	**-3.83**	**0.00**
s_pctcomdral	**-0.13**	**-0.02**	**3.49E-03**	**-5.91**	**0.00**
s_ehindex	**-0.24**	**-0.34**	**0.03**	**-11.07**	**0.00**
c_allresper100	**-0.32**	**-1.02**	**0.08**	**-13.51**	**0.00**
s_mal2femtrips					0.56
c_pctcondores					0.69

Above model: R-squared: 0.88 ; Adjusted R-squared: 0.88; F-statistic: 351.292 on 11 on 570 DF, p-value: 0.000
(Full model: R-squared: 0.94; Adjusted R-squared: 0.92; F-statistic: 70.209 on 100 and 482 DF, p-value: 0.000)

Variable	Standardized	Coef	Std. Error	t value	Pr(>|t|)
ln(trips_flow)					
(Intercept)	**0.00**	**6.42**	**0.70**	**9.11**	**0.00**
s_pctmultihu	**0.26**	**0.02**	**1.74E-03**	**10.21**	**0.00**
s_jobaccess	**0.17**	**1.69E-06**	**3.04E-07**	**5.56**	**0.00**
s_divtrips_nd	**0.08**	**0.03**	**0.01**	**4.61**	**0.00**
s_bikelanedensity	**0.04**	**0.03**	**0.01**	**2.36**	**0.02**
c_pctcomwalk	**-0.11**	**-0.02**	**4.40E-03**	**-4.33**	**0.00**
s_avgdist2div	**-0.12**	**-0.13**	**0.03**	**-3.88**	**0.00**
s_pctcomdral	**-0.14**	**-0.02**	**3.45E-03**	**-6.08**	**0.00**
s_ehindex	**-0.24**	**-0.34**	**0.03**	**-11.09**	**0.00**
c_allresper100	**-0.32**	**-1.00**	**0.07**	**-13.48**	**0.00**
s_mal2femtrips					0.34
c_pctcondores					0.68

Above model: R-squared: 0.88; Adjusted R-squared: 0.88; F-statistic: 359.024 on 11 and 571 DF, p-value: 0.000
(Full model: R-squared: 0.94; Adjusted R-squared: 0.92; F-statistic: 69.339 on 100 and 482 DF, p-value: 0.000)

housing units is associated with a 1.80 percent increase in Divvy rentals and a 10,000 increase in total jobs accessible is associated with a 1.84 percent increase in rentals. Whereas, a one percent increase in the percentage of nonwhite population residing within 1/4 mile of a Divvy station is associated with a 1.3 percent decrease in Divvy rentals from that station. The above models also show that the network and schedule-based indicators of public transit and job accessibility have stronger predictive power than more simplistic, proximity- and frequency-based indicators.

IV. CONCLUSION

The planning and development of bicycle-sharing systems continues to grow rapidly around the world, within both urban and suburban areas. Because the US started rather late in this process, performance data of these systems has only recently become available, researchers are only beginning to understand the factors underlying system usage over time. This study contributes to a growing literature on bicycle-sharing systems by exploring the spatio-temporal characteristics of expansion, service gaps as well as both local- and community-level factors that may influence trip generation, destination decisions and overall bikeshare activity flows.

The current study found that the two major expansions of the Divvy system in 2015 and 2016, which now extends several miles from the central business district including the suburbs of Evanston and Oak Park, has fueled gains in the number of users and frequency of rides for the system as a whole. These expansions have also extended access to the Divvy system across select communities with greater economic hardship over time, albeit at incrementally lower bikeshare station densities. Regression results suggest that usage rates are considerably lower among lower income communities of color suggesting that considerable barriers to bikeshare exist across throughout the city and a need to continue and expand equity-based programs to increase ridership in transportation disadvantaged communities.

Regression model results show that neighborhood design, accessibility, socioeconomic and related bikeshare characteristics all have considerable predictive power in explaining variability in Divvy bikeshare activity. The study also found that an extensive gender gap exists among Divvy riders, with males logging over three times the number of trips as females. Therefore, improving ridership throughout the system will likely require a transparent, multi-faceted approach informed by multiple stakeholder groups and the systematic tracking and reporting of key operations and performance information.

REFERENCES

1. Meddin, R. The Bike-Sharing Blog: The Bike-Sharing World at the End of 2016. The Bike-sharing Blog, Jan 25, 2017.
2. NACTO. Bike Share in the US: 2010-2016. *National Association of City Transportation Officials*. https://nacto.org/bike-share-statistics-2016/. Accessed Jan. 10, 2017.
3. DeMaio, P. Bike-Sharing: History, Impacts, Models of Provision, and Future. *Journal of Public Transportation*, Vol. 12, No. 4, 2009, p. 3.
4. ITDP. *The Bike-Share Planning Guide*. Institute for Transportation and Development Policy, 2013.
5. Fishman, E., S. Washington, and N. Haworth. Bike Share: A Synthesis of the Literature. *Transport Reviews*, Vol. 33, No. 2, 2013, pp. 148–165. https://doi.org/10.1080/01441647.2013.775612.
6. Barth, M., and S. Shaheen. Shared-Use Vehicle Systems: Framework for Classifying Carsharing, Station Cars, and Combined Approaches. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1791, 2002, pp. 105–112. https://doi.org/10.3141/1791-16.
7. Beatley, T. *Green Urbanism: Learning From European Cities*. Island Press, 1999.
8. McNeil, N., J. Macarthur, and J. Dill. *Breaking Barriers to Bike Share: Insights from Residents of Traditionally Underserved Neighborhoods*. Publication NITC-RR-884b. Transportation Research and Education Center, Portland State University, 2017, p. 232.
9. TED Books, Ed. *City 2.0: The Habitat of the Future and How to Get There*. TED Conferences, 2013.
10. Townsend, A. M. *Smart Cities: Big Data, Civic Hackers, and the Quest for a New Utopia*. W. W. Norton & Company, 2013.
11. Wolfe, C. R. *Urbanism Without Effort*. Island Press, 2013.
12. Wiedel, S., C. Hurley, K. Briski, S. Kubly, and K. Haley. Planning for New and Expanding Bikeshare Systems. Chicago, IL, Jun 09, 2014.
13. Klein, G., and D. Vega-Barachowitz. *Start-Up City: Inspiring Private and Public Entrepreneurship, Getting Projects Done, and Having Fun*. Island Press, Washington ; Covelo ; London, 2015.
14. TDG, and PBIC. *Bike Sharing in the United States: State of the Practice and Guide to Implementation Toole Design Group (TDG) and Pedestrian and Bicycle Information Center (PBIC)*. US DOT Federal Highway Administration, 2012, p. 68.
15. Shaheen, S., Elliot W. Martin, Nelson D. Chan, Adam P. Cohen, Mike Pogodzinski, and Susan A. Shaheen. *Public Bikesharing in North America During a Period of Rapid Expansion: Understanding Business Models, Industry Trends and User Impacts*. Publication 12–29. Mineta Transportation Institute, 2014.
16. NACTO. *Bike Share Station Siting Guide*. National Association of City Transportation Officials, 2016.
17. Bullard, R. D., and G. S. Johnson. *Just Transportation : Dismantling Race and Class Barriers to Mobility*. New Society Publishers, Gabriola Island, BC, 1997.
18. Bullard, R. D. The Anatomy of Transportation Racism. In *Highway Robbery: Transportation Racism and New Routes to Equity* (R. D. Bullard, G. S. Johnson, and A. O. Torres, eds.), South End Press, Cambridge.
19. Day, K. Active Living and Social Justice: Planning for Physical Activity in Low-Income, Black, and Latino Communities. *Journal of the American Planning Association*, Vol. 72, No. 1, 2006, pp. 88–99.
20. Fishman, E. Bikeshare: A Review of Recent Literature. *Transport Reviews*, Vol. 0, No. 0, 2015, pp. 1–22. https://doi.org/10.1080/01441647.2015.1033036.
21. League of American Bicyclists. *The New Majority is Pedaling Toward Equity*. 2013.
22. Smith, C. S., J. Oh, and C. Lei. *Exploring the Equity Dimensions of US Bicycle Sharing Systems*. Publication TRCLC 14-01. Transportation Research Center for Livable Communities, 2015.
23. McNeil, N., J. Macarthur, and J. Dill. *Breaking Barriers to Bike Share: Insights from Bike Share Users*. Publication NITC-RR-884c. Transportation Research and Education Center, Portland State University, 2017, p. 118.
24. CMAP. GOTO 2040.

25. Meekins, S., M. Whitcomb, and T. Garibay. Design and Analysis of Chicago's Bike Share System. Chicago, IL, Jun 06, 2014.
26. Friedman, S. M., M. Adamson, P. Cleiman, T. Arenovich, K. Oleksak, I. M. Mohabir, R. Ta, and K. Reiter. Helmet-Wearing Practices and Barriers in Toronto Bike-Share Users: A Case-Control Study. *Canadian Journal of Emergency Medicine*, Vol. FirstView, No. Supplement-1, 2015, pp. 1–9. https://doi.org/10.1017/cem.2015.22.
27. Kraemer, J. D., J. S. Roffenbender, and L. Anderko. Helmet Wearing among Users of a Public Bicycle-Sharing Program in the District of Columbia and Comparable Riders on Personal Bicycles. *American journal of public health*, Vol. 102, No. 8, 2012, pp. e23–e25.
28. Rainer-Harbach, M., P. Papazek, B. Hu, and G. R. Raidl. Balancing Bicycle Sharing Systems: A Variable Neighborhood Search Approach. In *Evolutionary Computation in Combinatorial Optimization* (M. Middendorf and C. Blum, eds.), Springer Berlin Heidelberg, pp. 121–132.
29. Siavash Shahsavaripour. Different Methods of Redistributing Bike among the Station: A Mathematical Solution in Order to Find Critical Stations. *American Journal of Environmental Engineering*, Vol. 5, No. 1, 2015, pp. 21–31.
30. Faghih-Imani, A., N. Eluru, A. M. El-Geneidy, M. Rabbat, and U. Haq. How Land-Use and Urban Form Impact Bicycle Flows: Evidence from the Bicycle-Sharing System (BIXI) in Montreal. *Journal of Transport Geography*, Vol. 41, No. Supplement C, 2014, pp. 306–314. https://doi.org/10.1016/j.jtrangeo.2014.01.013.
31. Martin, E. W., and S. A. Shaheen. Evaluating Public Transit Modal Shift Dynamics in Response to Bikesharing: A Tale of Two U.S. Cities. *Journal of Transport Geography*, 2014. https://doi.org/10.1016/j.jtrangeo.2014.06.026.
32. Rixey, R. A. Station-Level Forecasting of Bike Sharing Ridership: Station Network Effects in Three U.S. Systems. Presented at the TRB 92nd Annual Meeting, Washington DC, 2013.
33. Aysha Cohen. *Equity in Motion: Bikeshare in Low-Income Communities*. District Department of Transportation (DDOT), UCLA Institute of Transportation Studies, 2016, p. 88.
34. Corcoran, J., T. Li, D. Rohde, E. Charles-Edwards, and D. Mateo-Babiano. Spatio-Temporal Patterns of a Public Bicycle Sharing Program: The Effect of Weather and Calendar Events. *Journal of Transport Geography*, Vol. 41, 2014, pp. 292–305. https://doi.org/10.1016/j.jtrangeo.2014.09.003.
35. Faghih-Imani, A., and N. Eluru. Incorporating the Impact of Spatio-Temporal Interactions on Bicycle Sharing System Demand: A Case Study of New York CitiBike System. *Journal of Transport Geography*, Vol. 54, 2016, pp. 218–227. https://doi.org/10.1016/j.jtrangeo.2016.06.008.
36. Greg Griffin. Connecting the Dots: Linking Bike Share with Transit—while Considering Equity Issues—requires a Big-Picture Approach. American Planning Association, April, , 2017.
37. Sheller, M. Racialized Mobility Transitions in Philadelphia: Connecting Urban Sustainability and Transport Justice. *City & Society*, Vol. 27, No. 1, 2015, pp. 70–91. https://doi.org/10.1111/ciso.12049.
38. Singhvi, D., S. Singhvi, P. I. Frazier, S. G. Henderson, E. O. Mahony, D. B. Shmoys, and D. B. Woodard. Predicting Bike Usage for New York City's Bike Sharing System. *Association for the Advancement of Artificial Intelligence*, 2015.
39. Jia, Z., G. Xie, J. Gao, and S. Yu. Bike-Sharing System: A Big-Data Perspective. Presented at the International Conference on Smart Computing and Communication, 2016.