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New Equity Inputs to Prioritize Bikeshare Infrastructure Allocation: Learning From the COVID-19 Period

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Abstract

From "pop-up" road closures to decreased transit frequencies, the COVID-19 pandemic has changed the overall supply of transport options. Even in the absence of a change in bikeshare supply, the pandemic provides a "natural experiment" under which we can assess changes in bikeshare use across diverse communities in response to transportation system changes. The pandemic offers a unique moment to particularly measure changes in use for low socioeconomic status (SES) populations as historically limited deployments of bikeshare in low-income neighborhoods limit evaluation of key metrics for this population. For low SES users to realize greater accessibility through bikeshare, they may need to take relatively longer trips, given the sparse nature of the network in low-income areas and the existing inequitable geography of opportunities in urban environments in the United States. As such, we measure the effect of the COVID-19 pandemic on average daily bikeshare trip durations in Philadelphia, PA—the major city with the highest poverty rate in the United States. Through an interrupted time series approach, we find that the effect of the pandemic on trip duration for all bikeshare users is substantial (approximately 7–12 min increase), positive, and similar across diverse geographic areas. Importantly, these findings are persistent and statistically significant even when fitting models only on data from predominantly low SES areas of Philadelphia. This change pattern suggests first that low SES users exhibit roughly equal propensity as the general population to take longer trips, and second that bikeshare can provide a resilient, equitable travel mode.

Keywords

Bikeshare; COVID-19; regression discontinuity; equity; time series

Bikeshare programs, as a spatially dispersed and relatively affordable travel mode, hold potential to generate substantial gains in accessibility across the population (*1*, *2*). Yet, the siting of bikeshare stations has historically been centered on design variables including population density, income, and, for locations with existing bikeshare infrastructure, bikeshare ridership (*3*). Though certain metropolitan areas have begun to use equity criteria to cite new stations (*4–6*), the predominance of existing metrics place neighborhoods of lower socioeconomic status (SES) at a disadvantage for the allocation of new service. Related to this imbalance of supply, bikeshare users—though they may be more diverse than other cyclists across the metrics of gender (*7*), income, and race/ethnicity—still remain more white, higher income, and male than the general population (*8*). Furthermore, when bikeshare stations are present in lower income areas, high minority areas, or both, they appear to generate fewer trips (*9*). However, it is unclear if those from low SES backgrounds prefer to travel on other modes, or if they would choose to utilize a bikeshare system if it were more accessible and provided better access to

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opportunities. The barriers to the use of bikeshare for low SES populations is well documented, and include issues related to station proximity, means of payment, and gaps in the network leading to prohibitively long travel times (*1*, *10*, *11*). Given the predominate policy frameworks that prioritize siting docking stations outside low SES areas, there are limited examples that allow for observational data that can explore low SES users' propensity to change their use of bikeshare.

The COVID-19 pandemic did not bring about an instantaneous increase in bikeshare supply, but it did fundamentally change the transportation environment, for example in decreased transit frequencies (*12*) and "pop-up" road closures for active travel modes (*13*). In the absence of ample policy experiments from bikeshare operators, the COVID-19 pandemic provides a "natural experiment" under which we can evaluate changes in bikeshare use in communities with low SES, which provides signals of propensities for use. To do so, we must isolate the characteristics of bikeshare before and during the COVID-19 pandemic and statistically evaluate if the onset of the pandemic changed the trends seen in these characteristics. While "check outs"—trip frequency—might be an obvious variable to gauge the magnitude of use, a more nuanced analysis that provides insight into the accessibility gains afforded by bikeshare can be achieved by evaluating changes in trip duration (*14*). For low SES users to realize greater accessibility through bikeshare, they may need to take longer trips, given the sparse nature of the network in low-income areas and the existing inequitable geography of opportunities in urban environments (*15*).

In the following analysis we seek to investigate how the dynamics of the COVID-19 pandemic reflect in changes to bikeshare trip durations across varied socioeconomic and demographic areas, what these changes indicate for propensity for use, and the ways these changes exhibit bikeshare's capacity to provide resilience and redundancy for diverse users. We measure the effect of the onset of the COVID-19 pandemic on average daily bikeshare trip durations for the Indego bikeshare system in Philadelphia across neighborhoods to capture a range of low, medium, and high SES bikeshare users. Philadelphia features both a relatively long-running bikeshare system, and a highly racially and economically segregated geography (*16–22*), where low income, high minority neighborhoods are often concentrated and spatially distant from opportunities.

Qian and Niemeier (*23*) pointedly argue that, "For bikeshare systems to prove useful to disadvantaged communities, the way in which they are designed must shift from operationalizing systems that target certain demographics to designing systems that target gaps in accessibility." Methodologically, the interruptions in the pandemic offer an opportunity to define new inputs, beyond existing variables such as ridership or those derived from surveys or demand models (*24*, *25*), to inform the allocation of bikeshare infrastructure that supports broad-based accessibility gains. If during the pandemic we find that trip durations for low SES bikeshare users increased, this population exhibits high propensity to change use patterns, and could realize greater accessibility through this mode. Moreover, if trip durations for low SES users went up in a way that mirrors trends for the general population, such findings imply that bikeshare provided a necessary, redundant, and alternative travel mode during the pandemic; not only did the bikeshare system provide a mobility option, but also it provided resilience. Policy could build on these positive examples under initiatives that build more opportunities for using bikeshare services, such as comprehensive geographic expansions of bikeshare systems including to outlying, low SES areas.

To derive new accessibility inputs, we utilize an interrupted time series approach that measures trip durations over time and isolates the effect of the pandemic on the change in trip duration, while controlling for seasonal variation. This effect is first measured at the system-wide level to determine whether average trip durations change substantially during the COVID-19 period. Next, time-series models are fit on subsets of the data based on the geographic location of origin docking stations. We group the data based on the convenient political geography of Philadelphia's planning districts, which describe highly varied socio-economic and demographic areas of the city. We find that the effect of the COVID-19 pandemic on trip duration is substantial and positive both at the system level and across all the planning districts analyzed. Our findings suggest that, first, users of low SES substantially increased their trip durations during the pandemic, and, second, that all populations, regardless of SES, increased bikeshare travel times in much the same way. Together, these findings suggest two important lessons for bikeshare policy. First, low SES users exhibit propensities for longer travel times that may be necessary to realize accessibility gains through bikeshare; this suggests that interventions in more outlying geographic areas may yield positive benefits for users previously excluded from the system. Second, bikeshare provided broad-based benefits to a range of population groups during the crisis; this signals that bikeshare provided a level of necessary system redundancy and transport resiliency during the pandemic. Regardless of the rationale for trip making—recreation, commuting, or otherwise—users across the population spectrum dramatically increased use patterns, which highlights the important role for bikeshare as part of a large suite of mobility options. Planners can build on this example by broadly expanding the opportunities to utilize bikeshare services across diverse geographies and build on the positive energy generated around bikeshare use during the pandemic.

Relevant Literature

The growth and development of bikeshare systems is well documented in the literature (*1*, *2*, *26*). Scholars and policy makers have devoted specific energy to learn from underserved populations (*10*) and develop programs to diversify the population of bikeshare users (*27*). Though national surveys have found that low-income persons are disproportionately represented among cycling commuters (*28*), and some scholars have found that low-income status positively predicts utilitarian cycling (*29*, *30*), the characteristics of bikeshare users have trended toward the upper ends of the socioeconomic spectrum (*10*, *31–33*). Previous research on diversity and equity among bikeshare users has analyzed the ways that bikeshare system operators and public agencies can promote use (*34*) through initiatives that include: revisions to payment systems that previously excluded the unbanked (*35*), expanded hours of operation (*36*), and electrification of segments of the bike fleet (*37*). These policy interventions have only had, at best, mixed results at growing bikeshare use among low income populations, minority populations, or both (*38*). Of particular interest to this study, scholars have highlighted the need to equitably expand the spatial distribution of bicycle docking stations to lower-income, high minority populations, and/or otherwise disadvantaged areas (*39*). In studies in Canada (*40*) and Chicago (*41*), bikeshare stations are underrepresented in areas that are both low income and feature high minority populations. These studies suggest that there is a generally inequitable spatial distribution of bikeshare stations and that it is necessary, at least when using equity criteria (*5*, *42*, *43*), to orient the spatial allocation of bikeshare infrastructure toward promoting greater access as opposed to strictly increased ridership among already predominant higher SES user groups (*23*).

Following on the inequitable spatial distribution of bikeshare infrastructure, it is clear that not all of the population has access to the mobility and resiliency bikeshare can theoretically provide. The Federal Highway Administration explicitly calls for redundancy as a key element of building transport system resiliency (*44*), and bikeshare can increasingly be seen as one element of a necessarily redundant system. The primary area where scholars have highlighted this capacity for bikeshare to provide redundancy is during transit closures, when users do not have access to a major travel model and must utilize alternatives for their daily travel. In studies of two London tube strikes (*45*, *46*) and multiple rail closures caused by major track repairs in Washington, D.C. (*47*, *48*), scholars have found that bikeshare use increased during these interruptions, especially nearby subway stations, highlighting that bikeshare provides an important and used option that builds redundancy and resiliency in the transport system during major system interruptions. The massive disruptions posed to all mobility systems by the COVID-19 pandemic, with bicycling no exception (*49*), can yield new findings on the ways bikeshare systems provide redundancy across the population during crisis moments.

Bicycle use overall has generally increased during the pandemic, though the magnitude of this growth has differed across countries and between localities in the United States (*49*). Bikeshare specifically has exhibited more divergent patterns of use during the pandemic. After the first lockdown period in the United States from roughly late March to May 2020, during which time bikeshare use tended to decrease dramatically (*50*), many bikeshare systems saw use rebound fully, or even exceed 2019 levels (*51–53*). Some systems also saw trip durations increase substantially in this "rebound" period (*50*). Philadelphia, where we draw data for this study, saw both substantial increases in bicycling overall (*54*), as well as dramatic increases in bikeshare use during the pandemic, as compared to the previous year (*55*).

The extant literature is mixed on the ways bikeshare allowed for broad-based use across population groups during the pandemic. Hu et al. (*56*) find the areas of Chicago with a larger white population exhibit dampened "rebound" effects around bike-share use such that they utilize bikeshare at lower rates than the rest of the city after the peak "lock down" period. This finding suggests that non-white areas of Chicago may have been more dependent on bikeshare for mobility during the pandemic. In contrast, Nguemeni Tiako and Stokes (*57*) discuss the issues in the equity-oriented experiments bikeshare operators initiated during the pandemic, particularly how price-based initiatives are limited by the existing geography of bikeshare stations. These studies suggest that bikeshare can provide a resilient mode of transport during crisis periods (*52*, *56*), but the efficacy of the existing system may be limited in its reach to diverse users.

Research Design

In this paper we utilize origin-destination data from Philadelphia's Indego bikeshare system and a series of time-series models fit at the system and planning district level to measure the effect of the COVID-19 pandemic on average daily trip durations. Trip duration is specifically highlighted as this metric can approximate the propensity to take longer trips that may be necessary to yield accessibility gains for socially excluded (*58*, *59*) populations. Administratively collected data from "docked" bikeshare systems that utilize stations where users check in and out bicycles (*2*) generally provide two key indicators: trip frequency and trip duration. Frequency can be understood at the origin level as trip generation or at the destination level as attraction, but both describe the magnitude of use across space within a given system. Duration measures the intensity of use; in contrast to the number of trips generated, duration describes how much on average, by way of time in travel, a given user utilized the system's service. By specifying the same time series models across multiple well-established socio-economically and demographically diverse geographies, we can measure how socio-economic and demographic context may, or may not, yield different coefficients when regressing trip duration on indicator and interaction terms for the pandemic time period. If the coefficients' sign and magnitude are roughly constant, or at least positive and meaningful across diverse districts, this would suggest that bikeshare provided the assets of resilient mobility more widely and/or uniformly across diverse populations in the pandemic. This then would suggest that bikeshare has a capacity to provide social resilience that can be built on in the "post-pandemic" period.

Philadelphia provides a strong case-study for this analysis for four reasons: 1) the Indego system is well established and long running, having launched in 2016, meaning there is ample and publicly available data to define a time-series analysis; 2) Philadelphia exhibits a diverse population that also features substantive socio-economic and racial segregation such that there is dramatic variation in the population even at high level geographies like planning districts; 3) Indego has from the outset sought to prioritize equity in its programmatic structure and is an anchor member of the Better Bikeshare Partnership (*27*), and is currently embarking on an equity-oriented system expansion; and 4) The City of Philadelphia issued a clear "stay-at-home" order on March 15, 2020, which serves to define the beginning of the pandemic period in the time series. Together these features determine both the data framework and policy applications that suggest the importance of applying our research question and design to the Philadelphia example.

Data Preparation

Bikeshare ridership data and station information was obtained from the Indego trip database consisting of trip durations, station origin, and station destination for all trip-level itineraries in January 2016, when the Indego system began service, through September 2021, the most recently released data. Philadelphia currently features only "docked" bikeshare bicycles. The Indego system does not publicly provide any background data on its users beyond whether they hold a subscription and the type of subscription. Therefore, we utilize aggregate U.S. Census data for areas containing bikeshare stations to describe socioeconomic and demographic characteristics of locations that feature bikeshare service. This approach follows on robust examples in the literature that utilize census data to proxy for unknown characteristics of bikeshare users (*41*, *60*, *61*). These aggregate variables provide context for the social landscape in which the Indego bikeshare system currently operates in Philadelphia and describe differences between the various planning districts in the city. Census data is derived from the 2019 5-year American Community Survey and analyzed at the census tract level. Additionally, the publicly available Philadelphia planning district geographic boundaries are employed to aggregate bikeshare trips and socioeconomic and demographic variables to the district level. Key variables and definitions are provided in Table 1.

Philadelphia's planning districts feature highly differentiated socio-economic and demographic characteristics (Table 2; Figure 1*b*). For example, the census tracts within the Central district feature average median household incomes more than $30,000 higher than the city average and more than twice that of many of the districts that have bikeshare stations. The percent of non-white population varies even more dramatically, such that the West district nears 100% of the population non-white, while more than half the population in the South district is white. The range in variation of these key metrics across planning districts makes this geography a useful unit of analysis through which to measure the varied equity impacts of the pandemic on bikeshare use.

Each bikeshare trip's origin station is assigned to the census tract and planning district in which it is located. The spatial distribution of bikeshare stations across Philadelphia's census tracts and planning districts is presented in Figure 1. Like studies highlighted in the literature review, bikeshare stations are unevenly spatially distributed across Philadelphia. Large areas of the city feature no stations, while, even among the areas covered, docking stations cluster toward areas that feature higher incomes and lower minority populations, compared to the city average. Nearly 50% of stations are located in the high income/low minority Central district (see Table 3). Philadelphia's downtown (Central district) and university areas (which concentrate in the University Southwest, Central, and Lower North districts) feature substantial residential land uses nearby to education, medical, and commercial centers (*62*, *63*), such that residence area data as collected from the Census (Table 2) can reasonably approximate the characteristics of bikeshare users utilizing stations in these areas. While it

Table 1. Variables and Definitions

Variable	Definition	Units
Trip level variables		
Origin	Bikeshare station from which the bicycle was checked out	Longitude/latitude degrees
Destination	Bikeshare station at which the bicycle was returned	Longitude/latitude degrees
Trip duration	Time elapsed from check out at origin station to check in at destination station	Minutes
Time-series variables		
Time	Day and year combination for which trip durations are aggregated	Day + Year
Treatment	Indicator variable defining observations in the COVID-19 period	Binary (1 = Time $\geqslant$ March 15, 2020 / 0 = Time $<$ March 15, 2020)
Month	Month in which trip occurred	Month
Population context variables (defined for origin station location)		
Income	Median household income (2019 $)	Census tract
Unemployment	Percent of working age population (∞ 16 years of age) unemployed	Census tract
Non-white	Percent of population non-white	Census tract
Population density	Persons/square mile	Census tract
Car access	Percent of households without access to an automobile	Census tract
Bachelor's degree	Percent of population with a bachelor's degree or higher	Census tract
Planning district	Geographic unit of analysis employed by the Philadelphia City Planning Commission to conduct planning surveys, analyses, and interventions	District

appears that Indego is present across a wide range of planning districts (Figure 1*b*), this is to some extent skewed by districts like the River Wards that are quite large, but only feature one station at the edge of the district closest to the downtown area.

Trip durations are aggregated to the daily average for both the system and planning district level to create a longitudinal data set. Trip durations in the 95th percentile or those less than or equal to 1 min are removed as outliers. The average trip duration was roughly 15 min across the time series for the full system, while slightly lower in the pre-pandemic period (13.93 min), and higher (17 min) during the pandemic period (differences in means by treatment statistically significant at $p < .001$).

Methods

The use of "natural experiments," like the beginning of the pandemic, to measure changes in behavior is well documented in the literature on quasi-experimental research designs (*64*) and reflects how researchers can take advantage of exogenous events to isolate causal factors (*65*, *66*). One example of such an approach is the regression "discontinuity" framework using time-series data, often referred to an "interrupted time series" (*67*).

We specify a time-series model that utilizes ordinary least squares (OLS) to regress trip duration on indicator and interaction terms for the COVID-19 period, while controlling for seasonality. Though OLS models can be susceptible to autocorrelation when using time-series data, as we discuss in the results, the residuals in our final OLS model are generally random over time and when plotted against fitted values; therefore, we do not make any revisions to the OLS structure. The model in this paper is defined such that:

$$TripDuration = f(Time, Treatment, Time * Treatment, Month) \tag{1}$$

where *Trip Duration* is the average daily trip duration measured across all origin bikeshare stations in the geography of interest; *Time* is a continuous variable indicating days; *Treatment* an indicator term equal to "1" for all days that fall on or after March 15, 2020; *Time* $\times$ *Treatment* is the interaction term between time and the pandemic indicator; and *Month* is a series of indicator variables measuring the month in which the daily average trip duration was defined, meant to control for seasonal variation. We center *Time* at "0" for March 15, 2020 for ease of interpretation of the intercept and the pandemic indicator and interaction terms. The month of May is reserved as the comparison case for seasonality in the models as this month roughly describes the most ideal cycling conditions, at least weather wise,

Table 2. Mean Values for Population Context Variables

	PHL	Tracts w/ Bikeshare Stations	Central	Lower North	Lower South	River Wards	South	University Southwest	West	West Park
Income	4.59×10^4	5.91×10^4 (1.32×10^4)	7.86×10^4 (3.27×10^4)	3.22×10^4 (-1.37×10^4)	4.88×10^4 (2.89×10^3)	4.64×10^4 (4.51×10^2)	6.07×10^4 (1.48×10^4)	4.32×10^4 (-2.70×10^3)	3.49×10^4 (-1.10×10^4)	4.48×10^4 (-1.17×10^3)
Non-white	59.34	43.86 (−15.48)	34.22 (−25.12)	71.19 (11.85)	44.53 (−14.81)	42.47 (−16.87)	42.32 (−17.02)	69.12 (9.78)	92.31 (32.97)	85.07 (25.73)
Population density	1.10×10^4	1.49×10^4 (3.85×10^3)	2.83×10^4 (1.72×10^4)	2.42×10^4 (1.32×10^4)	4.24×10^3 (-6.83×10^3)	1.84×10^4 (7.32×10^3)	2.65×10^4 (1.54×10^4)	3.53×10^4 (2.43×10^4)	3.22×10^4 (2.12×10^4)	1.43×10^4 (3.18×10^3)
Unemployment	9.17	6.36 (−2.81)	4.25 (−4.92)	12.39 (3.22)	10.31 (1.14)	9.31 (0.14)	7.87 (−1.3)	8.31 (−0.86)	11.90 (2.73)	7.94 (−1.23)
Car access	30.07	37.83 (7.76)	36.15 (6.08)	42.97 (12.9)	29.21 (−0.86)	26.18 (−3.89)	31.73 (1.66)	44.15 (14.08)	43.98 (13.91)	32.67 (2.6)
Percent with Bachelor's degree	17.31	28.25 (10.94)	33.15 (15.84)	13.36 (−3.95)	14.46 (−2.85)	14.78 (−2.53)	21.57 (4.26)	19.43 (2.12)	12.13 (−5.18)	16.17 (−1.14)

Note: PHL = Philadelphia. Difference from Philadelphia mean reflected in parentheses.

in Philadelphia as it is generally neither too hot/humid nor too cold. Time-series regression models are fit on data defined for the entire Indego system, as well for each planning district in which there are bikeshare stations. All analyses are conducted using the open-source statistical software R (*68*).

Results

The time series for average bikeshare trip durations at the system and planning district levels are presented in Figure 2. Though we lack data on the exact demographic and socio-economic character of bikeshare users before and during the pandemic, there are clear differences in use, as measured by trip duration, across planning districts. As discussed earlier, these planning districts are quite different from one another in SES, but tend to reflect consistent population characteristics within a given district. While the general shape of the time series trend is similar across planning districts, and parallels the trend for the system overall, there are substantial differences across districts in the observed range of trip duration values. This is presented in the varied trip duration values (on the y-axis) across the district level plots in Figure 2*b*, where, for example, the maximum average duration in the Lower South district hovers around 60 min, compared to 30 min in the Lower North district. Regardless, there is a clear and dramatic increase in trip duration at the system level around the onset of the COVID-19 pandemic (Figure 2*a*). There appears to be no initial "decline" or rebound in the average trip durations in Philadelphia around the start of the pandemic. Instead, bikeshare trip times appear to have steadily and dramatically increased at the start of the pandemic—with growth tapering off only midway through the summer of 2020. Trip durations appear to have returned roughly to the pre-COVID-19 pattern in 2021.

Though there is variation in the trend, this same general pattern of substantive increases in trip durations during the pandemic holds across the time-series patterns defined for each planning district (Figure 2*b*). When aggregated to the district level, there is far greater variability and volatility in average trip durations in certain districts like West Park compared to others like the South district that are more clustered. Planning districts that feature a truncated time series reflect that there were no bikeshare stations in those districts at that time period.

These differences in the range, variability, and volatility in the time-series patterns across districts can be largely explained by three factors: (1) the number of stations in each planning district; (2) the distance from stations in a given planning district to other stations in the system; and (3) the presence of "Round Trip" trips. The

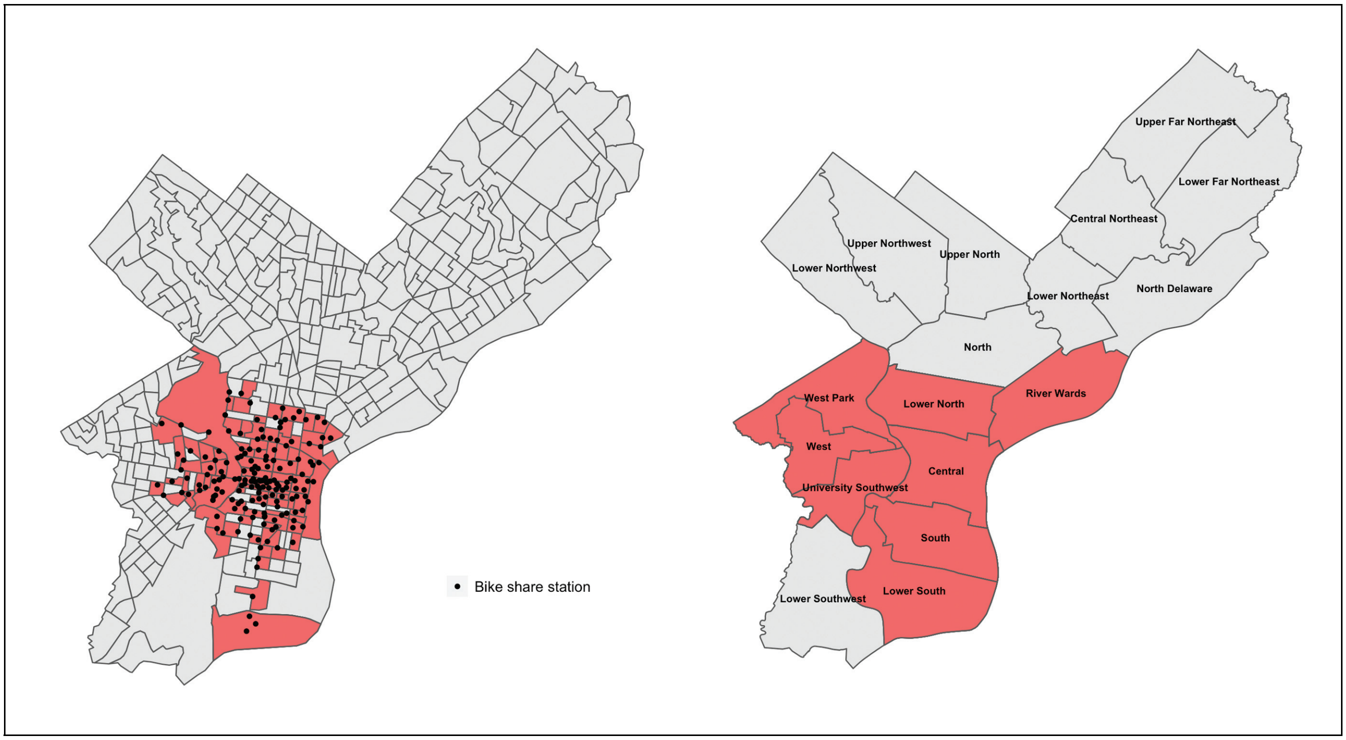

Figure 1. Indego Bikeshare station locations across Philadelphia: (*a*) census tracts and (*b*) planning districts.
Note: Tracts and planning districts with bikeshare stations highlighted.

Table 3. Distribution of Bikeshare Stations Across Planning Districts

Planning district	Bikeshare stations (*n*)	Bikeshare stations (%)
Central	84	49.70
University—Southwest	23	13.61
South	20	11.83
Lower North	27	15.98
West	7	4.14
West Park	3	1.78
River Wards	1	0.59
Lower South	4	2.37

limited number of stations in more outlying districts (see Figure 1 and Table 3) are more susceptible to swings in average values given that there are generally fewer observations from which to draw measures of central tendency. In addition, these same outlying districts have limited opportunities for mid-range trip durations; compared to the Central district where the abundance of stations means that trip times can take on a more continuous range of values based on destination; in outlying districts, gaps in the spatial distribution of docking stations mean "one-way" trips can either cover short or long durations. Finally, the presence of "Round Trip" trips—where a user checks out and returns a bicycle at the same docking station—may be further driving the volatility in certain districts. For example, the West Park bikeshare stations are located near to Martin Luther King Drive, the primary example in Philadelphia where roadways were closed to automobiles for pedestrian and cyclists' use (*13*) during the pandemic (*69*). This roadway has seen great use in the pandemic and proximity to such areas may yield longer, round-trip, recreational tours.

Recall that the planning districts exhibit quite different socioeconomic and demographic contexts (Table 2). Across these varied social contexts, the difference in trip durations before and during the pandemic ranges from around 2 to 6.5 min in a given planning district (all differences in means significant at $p < .001$), compared to a difference of about 3 min at the system-level ($p < .001$). The shape of the distributions of trip durations differs between districts and compared to the system level (Figure 3); nonetheless, as seen in both the time-series and "pre-COVID-19/COVID-19" analyses of trip duration, the pandemic yields positive and statistically significant increases in trip duration across each of the diverse geographic areas.

For all months, average trip durations were higher during the COVID-19 period as compared to the same month before the pandemic (Figure 4). These differences are most dramatic in the spring and summer months, suggesting that an initial wave of much longer trips

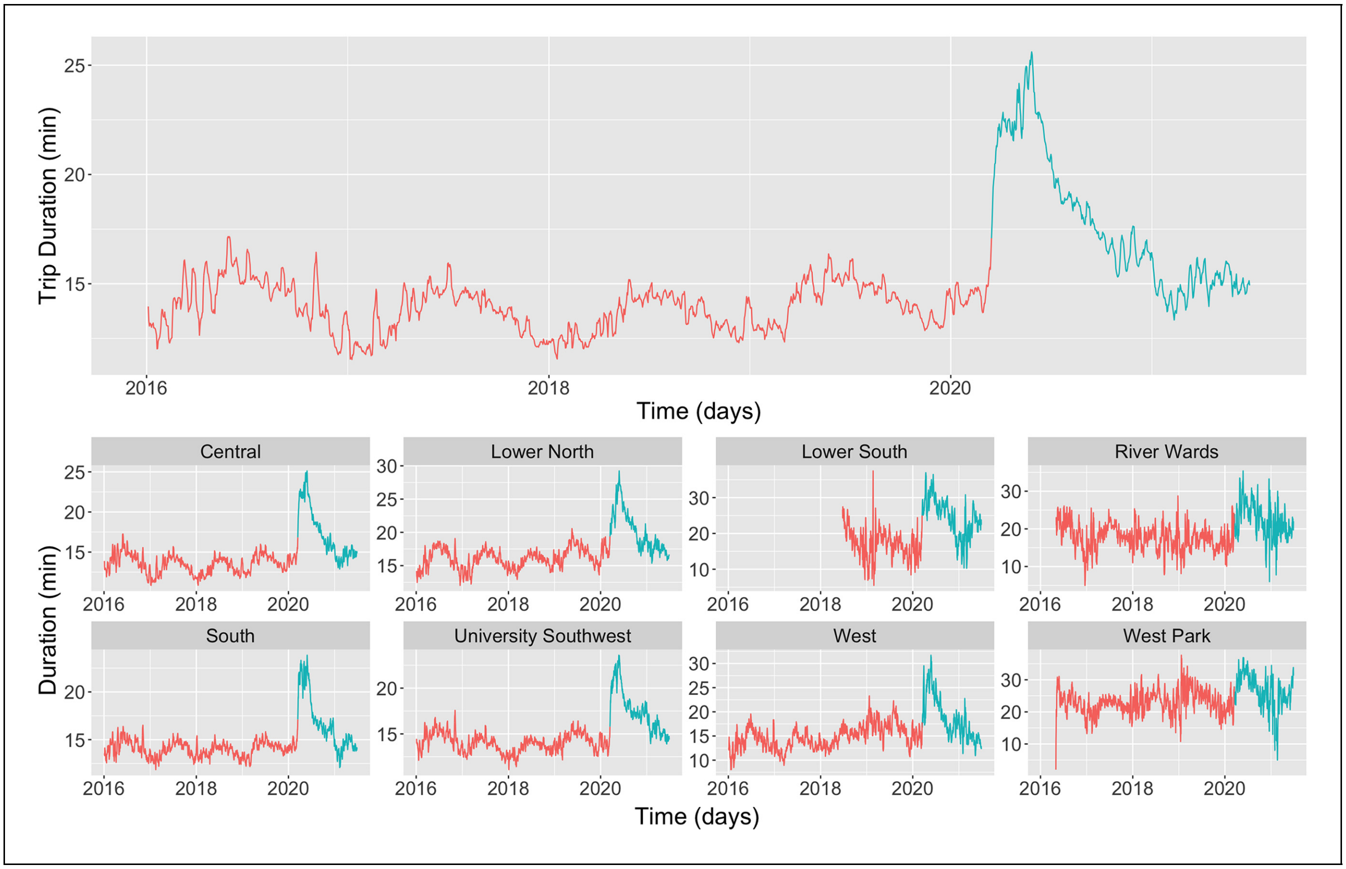

Figure 2. Time series for average daily bikeshare trip duration/day by treatment period for: (*a*) the system level and (*b*) by planning district.

Note: y-axis range varies across planning districts. Seven day rolling averages presented.

dampened as both the weather became less hospitable to cycling and other transportation options like transit returned to more regular schedules. The magnitude of the difference in trip durations across the same month before and during the pandemic range from a minimum of less than 1 min in February to around 5 min in May (all differences in means significant at $p < .01$).

The time-series regression models reinforce the findings of the "pre COVID-19/COVID-19" analyses and add nuance as to the effect of the pandemic on trip durations. Table 4 provides four models fit on data defined at the system level. Model 1 regresses average trip duration only on time, Model 2 introduces month fixed effects to control for seasonality, Model 3 includes the indicator term for the COVID-19 period, and Model 4, the final model, adds the interaction term for the indicator term and time. This iterative model building approach allows for a close analysis of the introduction of new covariates on coefficient sign and magnitude and builds on previous model building approaches in the literature (*20*). The residuals for Model 4, our final model, appear to be mostly random when plotted against time (Figure 5*a*) and against the fitted values (Figure 5*b*), which suggests no substantive autocorrelation that would require model specification corrections; we therefore directly interpret and discuss the OLS results.

The intercept/constant values across each model reflect the trip duration on March 15, 2020 given the other variables in the model. For example, in Model 3, the intercept is at 14.91 min and the binary indicator for the COVID-19 period shifts this intercept upwards by roughly 3.45 min. Also, note that the direct effect of time on trip duration is very small and changes signs across model iterations. This suggests that, if not for the pandemic, trip durations are roughly constant when accounting for seasonality.

The coefficients in Model 4 suggest a substantial and positive direct effect of the pandemic indicator on daily average trip durations of approximately 7.46 min. This suggests there is a dramatic effect of the pandemic on bikeshare use, at least in the immediate period after the onset of the public health crisis. However, the interaction term between time and treatment features a negative sign and is also statistically significant. The negative sign on the interaction term suggests a return to more normal bikeshare use during later periods of the pandemic; put

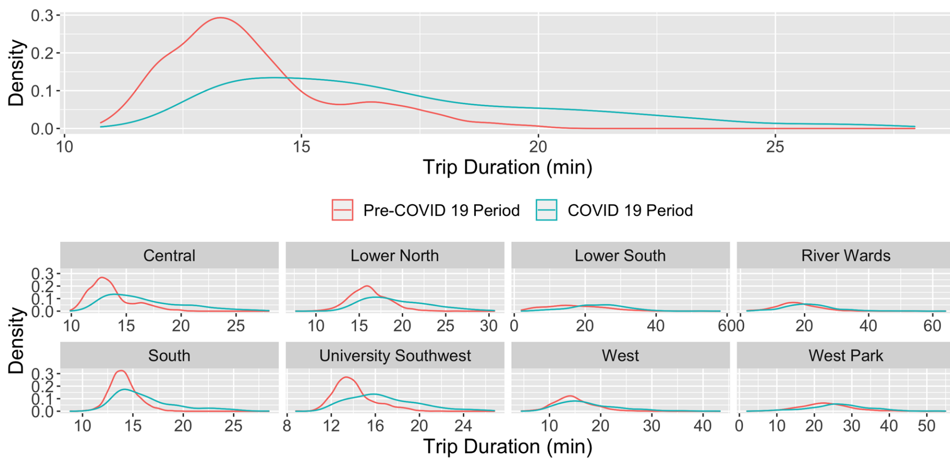

Figure 3. Density distribution of average daily bikeshare trip duration by treatment period for: (*a*) the system level and (*b*) by planning district.
Note: x-axis varies across subsets.

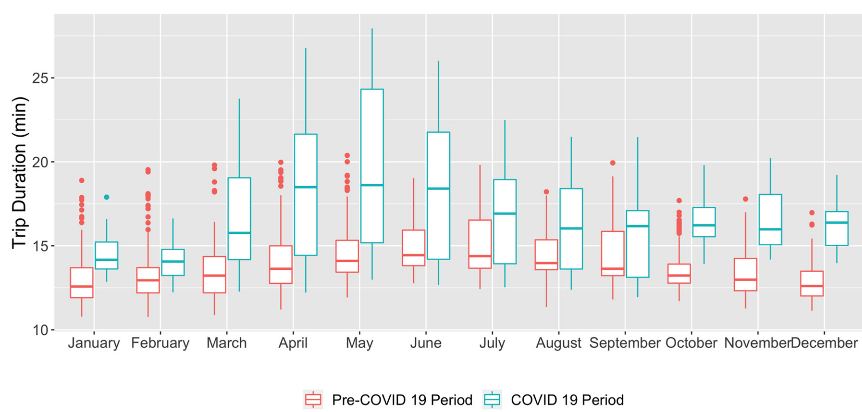

Figure 4. Boxplots that describe average trip durations for the system level by treatment period across months.

differently, there do not appear to be clear sustained positive effects. We discuss possible implications of the interaction term in the conclusion. Though not a primary finding for this research, the sign and significance for the month fixed effect terms suggest that users took longer bikeshare trips in the months of May and June, which adds further examples to the literature that describes how bikeshare use increases during periods of more pleasant weather (*70*, *71*).

The findings for our final model specified using data from each of the eight planning districts suggests that the effect of the pandemic is similar across these quite different geographic areas and mirrors the model results at the system level (Table 5). Recall, these planning districts reflect varied social characteristics (Table 2). Our approach of fitting separate models within each district, so as to account for these differences in socio-economic and demographic features, builds on multiple examples in the transportation field that fit the same model across multiple subgroups in the data (*72*, *73*).

The coefficient on the treatment variable defining the start of the pandemic is positive and statistically significant across all eight models and ranges from roughly 5 min (West Park) to nearly 12.5 min (Lower South). Similarly, the interaction term is negative and statistically significant across all models. Given both the socioeconomic and demographic diversity of these districts, and the range in variability and volatility across the time series patterns when defined at the district level, these stable and constant effects in the regression models

Table 4. Time Series Models Results at the System Level

	Dependent variable:			
	Trip duration			
	(1)	(2)	(3)	(4)
Time	0.001*** (0.0001)	0.001*** (0.0001)	−0.001*** (0.0001)	0.0002* (0.0001)
January	na	−2.974*** (0.251)	−2.618*** (0.231)	−2.383*** (0.179)
February	na	−2.760*** (0.257)	−2.358*** (0.236)	−2.058*** (0.182)
March	na	−1.871*** (0.251)	−1.729*** (0.230)	−1.719*** (0.178)
April	na	−0.662*** (0.253)	−0.721*** (0.232)	−0.872*** (0.179)
June	na	−0.357 (0.253)	−0.298 (0.232)	−0.148 (0.179)
July	na	−0.827*** (0.251)	−0.709*** (0.230)	−0.408** (0.178)
August	na	−1.351*** (0.251)	−1.173*** (0.230)	−0.718*** (0.178)
September	na	−1.664*** (0.253)	−1.427*** (0.232)	−0.821*** (0.180)
October	na	−2.070*** (0.263)	−1.667*** (0.242)	−1.772*** (0.187)
November	na	−2.323*** (0.265)	−1.861*** (0.244)	−1.886*** (0.189)
December	na	−2.845*** (0.263)	−2.324*** (0.242)	−2.267*** (0.187)
Treatment	na	na	3.452*** (0.173)	7.458*** (0.171)
Time: Treatment	na	na	na	−0.017*** (0.0005)
Constant	15.439*** (0.073)	17.005*** (0.182)	14.913*** (0.197)	15.364*** (0.153)
Observations	2,098	2,098	2,098	2,098
R^2	0.097	0.223	0.347	0.611
Adjusted R^2	0.097	0.218	0.343	0.608
Residual standard error	2.599 (df = 2096)	2.417 (df = 2085)	2.216 (df = 2084)	1.711 (df = 2083)
F statistic	224.995*** (df = 1; 2096)	49.830*** (df = 12; 2085)	85.226*** (df = 13; 2084)	233.653*** (df = 14; 2083)

Note: na = not applicable; df = degrees of freedom; *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

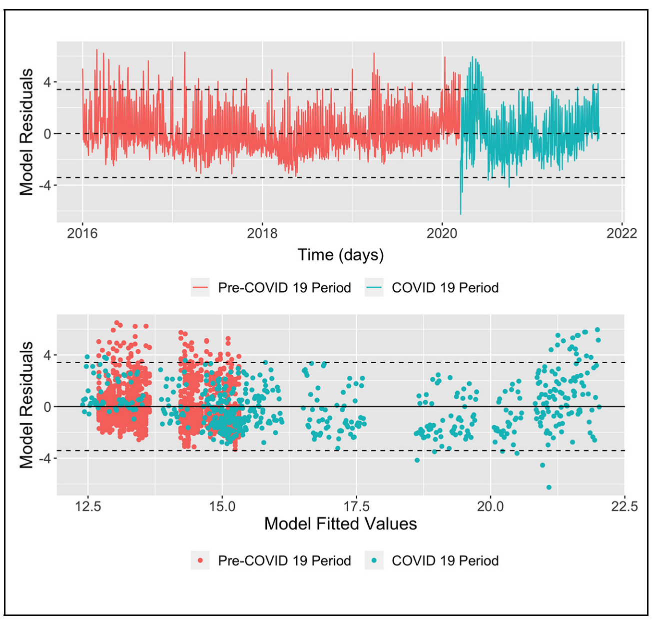

Figure 5. Model residuals for final model of trip duration at the system level plotted against: (*a*) time, and (*b*) model fitted values.
Note: dashed lines reflect ± two standard deviations in residual values.

suggest a strong and consistent trend. Regardless of the population surrounding origin stations, and the variation in day-to-day averages, trip times went up in a substantial fashion during the pandemic period.

Conclusion

The findings suggest that bikeshare trip durations increased during the pandemic period across highly varied socioeconomic and demographic geographies. Based on the results for models fit in planning districts typified by low SES populations, we find that low SES users exhibit high propensities to increase their use of bikeshare and could reasonably realize accessibility gains that may necessitate longer travel times; programmatic system expansions in more distant geographic areas could therefore yield increased benefits for users formerly located beyond the reach of the system. We also find that diverse populations exhibit similar propensities to increase bikeshare use in the pandemic; users across the population dramatically increased use, foregrounding bikeshare as an important option in the larger landscape of mobility options. The results of the "pre COVID-19/ COVID-19" analyses and models suggest that bikeshare systems can provide not only redundancy in times of mobility interruptions, but also that this capacity can reach a broad-based constituency and thereby provide social resilience through greater mobility options. These

Table 5. Time Series Model Results by Planning District

	Dependent variable:							
	Trip duration							
	Central	University Southwest	South	Lower North	West	West Park	River Wards	Lower South
Time	0.0001 (0.0001)	−0.0001 (0.0001)	0.0001 (0.0001)	0.001*** (0.0001)	0.003*** (0.0002)	0.001*** (0.0005)	−0.002*** (0.0005)	−0.004** (0.002)
January	−2.502*** (0.196)	−1.725*** (0.191)	−1.715*** (0.156)	−2.443*** (0.215)	−1.151*** (0.414)	−3.838*** (0.863)	−2.885*** (0.832)	−7.154*** (1.150)
February	−2.092*** (0.200)	−1.596*** (0.194)	−1.575*** (0.159)	−2.311*** (0.219)	−1.239*** (0.420)	−3.950*** (0.890)	−1.335 (0.854)	−5.643*** (1.244)
March	−1.704*** (0.194)	−1.358*** (0.189)	−1.167*** (0.155)	−2.343*** (0.213)	−1.438*** (0.408)	−3.388*** (0.816)	−2.755*** (0.815)	−4.644*** (1.121)
April	−0.849*** (0.196)	−0.706*** (0.190)	−0.465*** (0.156)	−1.443*** (0.214)	−0.923** (0.411)	−1.299 (0.797)	−1.378* (0.796)	−1.246 (1.099)
June	−0.146 (0.196)	−0.343* (0.190)	−0.136 (0.156)	0.128 (0.214)	1.197*** (0.411)	0.330 (0.753)	0.177 (0.751)	−0.448 (1.085)
July	−0.343* (0.194)	−0.576*** (0.189)	−0.419*** (0.155)	−0.415* (0.213)	0.885** (0.408)	−0.755 (0.749)	−0.178 (0.747)	−1.880* (1.033)
August	−0.730*** (0.195)	−0.674*** (0.189)	−0.656*** (0.156)	−0.599*** (0.213)	0.227 (0.409)	−0.841 (0.750)	0.477 (0.747)	−0.997 (1.032)
September	−0.846*** (0.197)	−0.785*** (0.191)	−0.500*** (0.157)	−0.915*** (0.216)	−0.188 (0.413)	−1.584** (0.758)	−1.138 (0.755)	−1.276 (1.043)
October	−1.858*** (0.204)	−1.308*** (0.199)	−1.118*** (0.163)	−2.029*** (0.224)	−1.495*** (0.429)	−3.917*** (0.788)	−1.915** (0.790)	−4.252*** (1.101)
November	−1.973*** (0.206)	−1.426*** (0.201)	−1.166*** (0.165)	−2.417*** (0.226)	−1.515*** (0.433)	−3.689*** (0.805)	−3.159*** (0.811)	−4.315*** (1.131)
December	−2.392*** (0.205)	−1.448*** (0.199)	−1.568*** (0.164)	−2.798*** (0.224)	−1.396*** (0.430)	−4.792*** (0.854)	−2.823*** (0.857)	−6.844*** (1.147)
Treatment	7.505*** (0.187)	6.806*** (0.182)	6.074*** (0.149)	7.327*** (0.205)	7.498*** (0.393)	5.331*** (0.743)	9.271*** (0.731)	12.449*** (0.914)
Time: Treatment	−0.017*** (0.001)	−0.015*** (0.0005)	−0.015*** (0.0004)	−0.019*** (0.001)	−0.027*** (0.001)	−0.014*** (0.002)	−0.013*** (0.002)	−0.016*** (0.003)
Constant	14.965*** (0.167)	14.989*** (0.163)	15.003*** (0.134)	18.377*** (0.183)	17.364*** (0.351)	26.288*** (0.675)	17.741*** (0.670)	19.372*** (1.003)
Observations	2,098	2,096	2,097	2,096	2,089	1,819	1,822	1,119
R^2	0.573	0.502	0.557	0.567	0.323	0.116	0.127	0.289
Adjusted R^2	0.570	0.499	0.554	0.564	0.319	0.109	0.120	0.280
Residual standard error	1.872 (df = 2083)	1.820 (df = 2081)	1.495 (df = 2082)	2.049 (df = 2081)	3.929 (df = 2074)	7.112 (df = 1804)	7.053 (df = 1807)	7.408 (df = 1104)
F statistic	199.421*** (df = 14; 2083)	150.113*** (df = 14; 2081)	187.063*** (df = 14; 2082)	194.841*** (df = 14; 2081)	70.736*** (df = 14; 2074)	16.862*** (df = 14; 1804)	18.716*** (df = 14; 1807)	32.106*** (df = 14; 1104)

Note: df = degrees of freedom; *p < 0.1; **p < 0.05; ***p < 0.01.

findings can inform bikeshare policy in at least the following three ways:

1. *Build on current use*. The increased trip durations are an inspiring impetus for bikeshare operators to consider their systems as "essential" mobility services, demonstrated by the magnitude of increased use during the pandemic. Though we hope that interruptions of the magnitude of the COVID-19 pandemic are rare, our findings make the case that bikeshare can quite dramatically absorb and adapt to exogenous circumstances. In areas with high and low densities of docking stations and different population characteristics, trip durations all increased substantially during the pandemic, signaling a general trend that bikeshare use gravitated toward a longer mean. Bikeshare system operators may benefit by conducting qualitative interviews with users as to what drove the change in trip duration during the pandemic and utilize these lessons to support policies that expand service (new stations), access to opportunities (electrification), or both.
2. *Link with new, safe physical infrastructure*. Consider the road closure of Martin Luther King Drive in Philadelphia. This 4.5-mile roadway previously served primarily as an auxiliary road to Interstate-76, and was used mo by motorists, often at unsafe speeds. With the closure to automobiles, this roadway immediately became a linear park, serving a largely low-income and non-white geographic area of Philadelphia. We believe part of the increase in trip durations, particularly in the West Park district, may be in part a result of such interventions. Further analysis of bikeshare use nearby "pop up" (*13*) closures and other safety interventions in the roadway infrastructure can help better understand these linkages.
3. *Serve the underserved*. Finally, our findings suggest that in times of crisis the benefits of bikeshare are widely distributed across diverse populations. Trip times increased around the pandemic in diverse socioeconomic and demographic geographic areas of Philadelphia. While much literature has shed light on the disproportionately white, upper income, and male background of the standard bikeshare user, these findings from the pandemic period suggest a different narrative of similar change in bikeshare use patterns across different population groups. These findings can serve as an impetus to grow the reach of bikeshare networks into previously underserved geographic areas. Philadelphia's Indego system has already taken strong steps in this direction through the recent system expansions into South and West Philadelphia (*74*).

While our findings on the social resilience capacity of bikeshare are robust across models, there are some limitations to our data and analytic approach. First, the most recently available data was collected amidst the ongoing pandemic. The lack of true post-COVID-19 data does not allow for clear statistical inference on sustained changes in trip durations following the pandemic. This raises issues, particularly with the interpretation of the interaction term in our models. If, after including post-COVID-19 periods of data, the interaction term is still negative and statistically significant, this would suggest an initial increase, but then a return to previous average trip durations. However, if the interaction term is no longer significant, or even positive, following the inclusion of post-COVID-19 data, this might suggest a sustained effect following the pandemic that features increases in travel times, yielding different policy lessons. We are eager to incorporate more recent periods of data to investigate these questions. Second, individual-level demographic and socioeconomic data is not publicly provided by Indego and features limited response rates even in internal surveys conducted by Indego that asked about such background characteristics (personal communication with Indego administrators, March 2020). Our assumptions about the equity implications of our analyses are thus based on context variables from geographies nearby to origin stations. However, these social indicators may not linearly match the characteristics of riders. Third, the aggregation to planning districts is politically important and convenient, but also analytically coarse. In future work it may make sense to instead define typologies at the more granular tract level, using clustering approaches based on social indicators (*21*). Models could then be fit within clusters to infer different effects (*20*). Fourth, and finally, we do not differentiate between utilitarian and recreational trips in this analysis. It may be the case that there are different effects of the pandemic across trip purposes.

In this paper, we articulate an approach that showcases the synthesis of publicly available data, open-source tools, and a parsimonious modeling structure (*75*) that yields new inputs which can help to move the planning of bikeshare systems away from "safe bets" in already served areas, toward a more expansive understanding of where equitable gains can be made through greater service provision. Bikeshare policymakers and operators will benefit by learning from the examples of use during the pandemic and should work to expand the capacity of bikeshare to provide broad-based accessibility, both in times of normalcy and crisis in the months and years to come.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: J. Davidson, M. Ryerson; data collection: J. Davidson, S. Nam, S. Karam, F. Koroma, E. Kim; analysis and interpretation of results: J. Davidson, S. Nam, S. Karam, F. Koroma, E. Kim, M. Ryerson; draft manuscript preparation: J. Davidson, S. Nam, S. Karam, F. Koroma, M. Ryerson. All authors reviewed the results and approved the final version of the manuscript.

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