Comparing Spatial Associations of Commuting versus Recreational Ridership Captured by the Strava Fitness App

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Transport Findings

Strava Metro data are used in bicycle planning, but there are concerns it overrepresents fitness activity. The data include a commute label, but spatial patterns of commuting versus recreational ridership are underexplored. Using spatial regression, we compare associations of Strava ridership by trip type. Commuting was associated with areas with more on-street infrastructure, universities, and higher bicycle crash density. Recreational ridership was higher in areas with older populations, more hills and major roads, and lower intersection density. Both trip purposes tended to be in areas with regional trails, off-street infrastructure, higher bicycle mode share, bridges, and proximity to the ocean.

Research Question and Hypothesis

Strava Metro data are being used in bicycling research but are critiqued for bias—both in demographic and trip type—related to who and how the app is used. How well Strava ridership reflects overall bicycle ridership depends on locational factors, for example, how busy a street is, if bicycling infrastructure exists, and safety (Livingston et al. 2020; Nelson et al. 2020). Bias can be addressed by using models that link Strava ridership to counts of all bicyclists, and adjusting for geographic covariates (Jestico, Nelson, and Winters 2016; Roy et al. 2019). Strava data also include a commute label, which may better align with overall ridership. However, there is limited understanding of how Strava trips labelled as commute versus recreation differ in terms of representativeness. Our goal is to understand how the commute label impacts data representativeness by comparing geographic covariates associated with Strava commute and recreational ridership. We hypothesize that commute and recreational ridership samples will be associated with different areas of a city and anticipate that, compared to recreational ridership, Strava data labelled as commute trips better represent overall ridership.

Methods and Data

Study area

The study area is the census metropolitan area (CMA) of Victoria, British Columbia, Canada, with a population of ~367,770 (Statistics Canada 2016) and a bicycle mode share of 6.6%, the highest among Canada’s CMAs (Statistics Canada 2017). Victoria has over 200 km of bicycling infrastructure including ~100 km of regional trails. These paths are the backbone of the bicycling network and are heavily used for both commuting and recreation.
Data and Analysis

We used spatial regression to identify associations between sociodemographic, network, and built and natural environment characteristics for each trip type, and for the pooled sample. The Strava Metro data are from January 1, 2016 - September 30, 2017, and include a spatial file representing the street network and tabular data with aggregate activity counts for each segment. An attribute provided by Strava Metro identifies the count of activities on each segment that were commute trips. We also had area-level summary statistics on the number of unique app users, age-gender distribution, and trip characteristics.

The geographical unit of analysis was the Statistics Canada Dissemination Area (DA; 400-700 people; n = 534). We operationalized Strava ridership as bicycle kilometers traveled (BKT), calculated by multiplying the activity count on each road segment by the segment length and summing the products for each DA (Hochmair, Bardin, and Ahmouda 2019). We standardized BKT by DA total road length and mapped results for each trip type compared to the pooled sample (Figures 1 and 2). Geographic covariates were identified based on previous studies using Strava data, relevance in bicycling studies using conventional data, or local importance to bicycling (Table 1).

We constructed three spatial error models using GeoDa 1.14 (Anselin 2019) and defined spatial neighbors using queen contiguity. The spatial error models use a Maximum Likelihood approach and treat spatially correlated residuals as a nuisance variable (Anselin 2009). The first and second models predicted DA commute and recreational BKT and the third predicted BKT for the pooled Strava sample.

Spatial analyses of areal data are often influenced by spatial autocorrelation (SAC)—the tendency for neighboring areas to have similar values. In ordinary least squares regression, spatial effects can lead to unreliable results as standard assumptions are violated (Anselin 2009). Spatial regression approaches include spatial lag and spatial error models, and model diagnostics indicate which is appropriate (Anselin 2009). We quantified SAC using Moran’s $I_p$, and used the Robust Lagrange Multiplier (LM) statistic to select the appropriate spatial regression model; the rule of thumb is to choose the model (lag or error) with the most significant LM test statistic (Anselin 2009). We also considered model fit ($R^2$ and AIC).

Findings

In Victoria, there were 12,971 unique Strava app users and 315,200 activities; 49% ($n = 155,252$) of activities were identified as commutes. Men accounted for 74.9% ($n = 9226$) of app users, and 64% of users ($n = 7,958$) were under age 55. Table 2 shows BKT descriptive statistics. Notably, BKT for recreational trips comprised nearly two-thirds of the total BKT (63.5%); so, while there were approximately equal numbers of commute and recreational activities, the recreational trips tended to be longer in distance.
Table 1. Geographic covariates used to model Strava bicycle kilometers travelled (BKT) at the dissemination area (DA) level

| Variable                      | Operationalization                                                                 | Relevance                                                                                                                                  | Source                                      |
|-------------------------------|-------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------|
| **Sociodemographic**          |                                                                                     |                                                                                                                                            |                                             |
| Bike commuters                | % of the population who bicycle to work                                             | Crowdsourced ridership patterns may be similar in areas where more people bicycle to work (Conrow et al. 2018)                                | Statistics Canada 2016 Census               |
| Male population               | % of the population who is male                                                     | Men associated with higher levels of bicycling (Aldred, Woodcock, and Goodman 2016) and Strava app usership                                    | Statistics Canada 2016 Census               |
| Median household income       | Quintile                                                                            | Higher and lower income associated with more bicycling (Pucher and Buehler 2006; Winters et al. 2007)                                        | Statistics Canada 2016 Census               |
| Post-secondary education      | % of the population with a post-secondary degree or diploma                         | Those with higher education more likely to bicycle (Winters et al. 2010)                                                                     | Statistics Canada 2016 Census               |
| Under 15 years                | % of the population under age 15                                                   | Children and older adults associated with lower rates of bicycling (Aldred, Woodcock, and Goodman 2016; Pucher et al. 2011)                   | Statistics Canada 2016 Census               |
| Over 65 years                 | % of the population over age 65                                                     | Higher neighborhood % of whites associated with more bicycling (Chen, Zhou, and Sun 2017); lower rates of bicycling investment in high % visible minority neighborhoods (Braun, Rodriguez, and Gordon-Larsen 2019) | Statistics Canada 2016 Census               |
| Visible minority              | % of the population who is a visible minority                                       |                                                                                                                                            |                                             |
| **Network**                   |                                                                                     |                                                                                                                                            |                                             |
| Arterial, collector, local    | % of the total neighborhood road network in each functional road class              | Road class and density influence bicycling safety and route choice (Fraser and Lock 2011; Winters et al. 2010)                                 | Capital Regional District                   |
| roads                         |                                                                                     |                                                                                                                                            |                                             |
| On-street bicycle infrastructure | % of the total neighborhood road network with on-street infrastructure              | Bicycling infrastructure associated with higher rates of bicycling (Fraser and Lock 2011); off-street paths associated with Strava ridership (Hochmair, Bardin, and Ahmouda 2019) | Capital Regional District                   |
| Off-street bicycle infrastructure | % of the total neighborhood road network with off-street infrastructure              |                                                                                                                                            | Capital Regional District                   |
| Regional trail                | Binary variable, 1 if regional trail network passes through DA                     | Important cycling infrastructure in the Victoria region                                                                                | Capital Regional District                   |
| Intersection density          | Count of intersections in 1 km of DA centroid                                        | Higher intersection density associated with more bicycling (Winters et al. 2010)                                                           | Canadian Active Living Environments (Can-ALE) |
| **Built & natural environment** |                                                                                     |                                                                                                                                            |                                             |
| Bridge                        | Binary variable, 1 if DA has a major bridge                                         | Bridges are important links between different parts of a street network (Boss et al. 2018; Hochmair, Bardin, and Ahmouda 2019)             | Capital Regional District                   |
| Distance to university        | Distance from DA centroid to nearest university                                      | Bicycling is higher around major destinations like universities (Krizek, Barnes, and Thompson 2009)                                         | British Columbia Open Data Catalogue       |
| Steep slopes                  | % of roads with                                                                     | Steep slopes impact route choice in utilitarian cycling and                                                                             | GeoBC                                       |
Strava activities labelled as commutes showed higher ridership levels in DAs that were closer to universities, had more on-street infrastructure, and higher bicycle crash densities. Recreational activities showed higher ridership in DAs with older populations, more hills and major roads (arterial and collector), and lower intersection density. Strava activities for commute or recreation showed similar levels of ridership in DAs with regional trails, more off-street infrastructure, higher bicycle mode share, bridges, and closer proximity to the ocean.

Using Strava data labelled as commute activities, instead of a pooled sample, may mitigate bias in Strava data and better represent ridership patterns of people of all ages and abilities. When using only the commute activities, we saw different spatial patterning in ridership and found that activities tended to be in areas with bicycle infrastructure, lower levels of safety, and around universities. Recreation activities were more common in areas with major roads, steep slopes, and lower intersection density—factors that are typically less preferred and less safe for bicycling (Teschke et al. 2012; Winters et al. 2010). Other important covariates were common across commute and recreational trips (regional trails, off-street infrastructure, bicycle mode share, bridges, and proximity to the ocean) and would be selected from either the commute or pooled sample. This suggests that if a planning exercise aimed to model overall ridership using Strava data and geographic covariates, a distinct set of covariates would be selected if only the commute data were used. In Victoria, commuting accounted for 49% of all Strava activities and 36.5% of the total distance (e.g., BKT). From other Strava analyses we learn the proportion of commute trips varies across cities (e.g., 21% in El Paso, Texas (Lee and Sener 2019), 85%
Figure 1. Strava commute BKT compared to the pooled sample (quintiles) in DAs (n = 534).

in Milan, Italy (Sunde 2019). If interested in modeling all ages and abilities ridership, researchers and practitioners should consider using only commute data, at least in cities where the sample is sufficiently large.

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Figure 2. Strava recreational BKT compared to the pooled sample (quintiles) in DAs (n = 534).
Table 3. Spatial regression estimates of DA Strava ridership (bicycle kilometers traveled, BKT) for trips labeled commute, recreation, and the pooled sample (all data combined).

| Outcome                      | Commute BKT | Recreational BKT | Pooled BKT |
|------------------------------|-------------|------------------|------------|
| **Spatial dependence diagnostics** |             |                  |            |
| Moran’s Ii                   | 8.7***      | 13.9***          | 12.2***    |
| Robust Lagrange Multiplier (lag) | 2.7         | 14.3***          | 6.7**      |
| Robust Lagrange Multiplier (error) | 12.2***     | 9.0*             | 13.2***    |
| R² (lag)                     | 0.6         | 0.6              | 0.6        |
| R² (error)                   | 0.6         | 0.6              | 0.6        |
| AIC (lag)                    | 8305        | 9019             | 9422       |
| AIC (error)                  | 8289        | 8986             | 9389       |
| **Geographic covariates**    |             |                  |            |
| **Sociodemographic**         |             |                  |            |
| Bike commuters               | 2120.6***   | 4861.2***        | 7030.5***  |
| Male population              | 1793.9      | 3542.4           | 5341.3     |
| Median household income      | 37.6        | 27.6             | 69.0       |
| Post-secondary education     | 616.8       | 916.4            | 1489.9     |
| Under 15 years               | -1182.7     | -237.5           | -1297.0    |
| Over 65 years                | 574.2       | 2015.9**         | 2623.0*    |
| Visible minority             | -291.2      | -850.6           | -1152.6    |
| **Street network**           |             |                  |            |
| Arterial road                | 608.0       | 3348.4***        | 4071.2***  |
| Collector road               | 211.0       | 1847.6**         | 2117.4*    |
| Local road                   | -245.2      | 277.1            | 39.2       |
| On-street bicycle infrastructure | 1572.9***   | 585.6            | 2087.9*    |
| Off-street bicycle infrastructure | 2589.7***   | 2904.0**         | 5488.3***  |
| Regional trail network       | 759.9***    | 734.7***         | 1475.0***  |
| Intersection density         | -3.2        | -20.9***         | -24.2***   |
| **Built and natural environment** |             |                  |            |
| Bridge                       | 765.9***    | 701.1*           | 1450.0**   |
| Proximity to university      | -29.0*      | -65.4            | -96.8*     |
| Steep slopes (more hills)    | 214.1       | 746.0*           | 927.9*     |
| Distance to shore            | -202.4***   | -509.7***        | -720.6***  |
| **Safety**                   |             |                  |            |
| Bicycle crash density        | 93.5***     | 52.7             | 140.1*     |
| Constant                     | -637.3      | -1087.3          | -1697.2    |
| Spatial error (Lambda)       | 0.5***      | 0.8***           | 0.7***     |

*** p < 0.001, ** p < .01, * p < 0.05

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