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| Paper | Methodologies | Takeaways |
| Enhancing equitable service level: Which can address better, dockless or dock-based Bikeshare systems?  San Francisco | -IDed “communities of concern” census tracts (with ACS data) by regional planning commission factors and concentration thresholds (different combinations defined to be considered a CoC)   * Minority – 70% * low income (<200% federal poverty level) – 30% * Limited English Proficiency – 20% * Zero-vehicle households -10% * Seniors 75+ - 10% * Disability – 25% * Single Parent Family – 20% * Severely rent-burdened – 15%   With different levels of concern indicated by how many factors/thresholds are met  -For comparative analysis of docked/dockless systems, chose service characteristics that are consistent including   * Service areas (quarter mile buffer around station, entire census tract if it’s in dockless area of service) * Number of available bikes (inferred from trip data, time between continuous trips with the same bike) * Bike idling time (inferred from trip data, time between continuous trips with the same bike)   + Daily bike availability average across all census tracts, then average metric for three months for every census tract. * Trip spatial distributions for both systems (provided by GoBike, for dockless JUMP bike (GBFS static vehicle ID) must identify rebalancing activity though by removing “trips” with long (4+ hour) durations or with increasing battery level) * Bike rebalancing activities (also inferred from trip data, does end position of one trip match start position of the next? There may be idling time before rebalancing activity/availability after, but this analysis doesn’t count this if a rebalance occurs in that timeframe) | * Docked bikeshare has smaller number of available bikes in all CoCs relative to others (t-test no significant difference) * Dockless bikeshare also had fewer available bikes per day in CoCs relative to others (t-test, also not significant)   + Greater average number of daily bikes in CoCs at a high level than in non-CoC tracts * For both docked and dockless bikeshare, idling time is significantly lower in CoCs (especially at high and highest concern levels) than in non-CoCs (bikes used more frequently in CoCs) * For docked, more rebalancing from non-CoC to CoC tracts than vice versa. For dockless there is slightly more rebalancing from CoCs to non-CoCs than vice versa. * Spatial distributions of origins and destinations for both systems * Trip length distributions by docked v dockless and type of trip (CoC to Non-CoC, Non-CoC to CoC, within CoCs, within Non-CoCs) * Elevation of trip origins, e-bike usage, and relationship to CoCs level of concern * Big one: dockless system provides a greater average number of available bikes in the CoCs at a high level than in non-CoCs, considering its total number of bikes (about half of the docked system) * Big limitation: unavailability of user information in JUMP Bike data – tourists could use instead of local residents in some CoC identified tracts |
| High impact prioritization of bikeshare program investment to improve disadvantaged communities' access to jobs and essential services  Chicago, Philadelphia | * Disadvantaged census tracts =   + Median household income   + % minority population (High, moderate, low thresholds)   + % households owning 0-1 vehicles (High, moderate, low thresholds) * Bike infrastructure from OpenStreetMap and local government data portals (length within each block group/block group area) (High, moderate, low thresholds) * Jobs data from LEHD database   + Low-wage jobs ($3333/month or less)   + Transit stations   + Grocery stores   + Hospitals   + Schools   + Used google maps API for two scenarios: walking and transit only, then assuming immediate access to bikeshare. Calculated travel times using standard walking, biking speeds and GTFS data. Text      Description automatically generated   Note: different weight factors assigned to different opportunities O based on percentages of trip purpose from survey results.   * Improvement in accessibility reported (high, moderate, and low). Graphed sensitivity of this for both disadvantaged and other areas with respect to max travel time and beta.   -Categories A-D created based on combinations of quantiles of disadvantaged areas, level of bike infrastructure, and potential for increased job/essential service access | -Areas of high priority for bikeshare stations, with analysis of existing bikeshare station locations in relation to identified disadvantaged census tracks to illustrate how this framework is different from others, and how service could improve for disadvantaged tracts  -limitations/potential improvements: with more info about traffic demand and transport mode split in disadvantaged areas, could have precise number of bike trips and created a more nuanced model for accurate estimation of accessibility  -Travel times averaged across block in accessibility analysis, only offer an approximate travel time between every block group pair  -travel cost of access was not considered, but should be as it is an essential factor of concern for disadvantaged populations  -doesn’t take into account dockless |
| Make e-scooters work with transit article |  | -Pre-pandemic about 8-12% of all trips were taken to connect with metrorail, and in June 2020 trips were longer in distance and duration, suggesting substitution (90% of trips in the Metro or CaBi service area could’ve been made by transit)  -There are strategies to promote collaboration- encouraging scooter deployment in unserved/underserved transit areas, stations/parking near transit stops and stations, bonus charging stations near transit stops also, integrated fare payment and bundled pricing |
| Spatiotemporal comparative analysis of scooter-share and bike-share usage T patterns in Washington, D.C. | -Lime data taken from API for the DC region, static vehicle ID trips found from 5 min scraping intervals for over 130 days  -Juicing trips are any 2+ hour trips, many are placed back into system between 4-8 am so the time distribution of trips identified as juicing was created as a check  -redistribution trips identified as any above the max trip speed, validated with the same time distribution of identified rebalancing trips to confirm that most happen between 3-4 pm on weekdays  -Docked capital bikeshare data available through Open Data portal, trip o/d and time included (also separated into members and casual users)  -Cosine similarity (CosSim) used to statistically assess degree of similarity in different days.  -Identified land use of the parcel where trips started/ended, evaluated percentage of trip types (ie residential > commercial, commercial > commercial, etc) and also evaluated types by hour of the week  -Also intersected with Traffic Analysis Zone polygons, computed Global Moran’s I for weekday and weekend trips to identify differences in spatial autocorrelation (basically do trips have a spatial pattern to them?). Made a map of normalized weekend trips-weekday trips for each TAZ to show where weekday trips dominate and weekend trips dominate  -To compare docked bikeshare (casual and member use), Watson’s U^2 two sample test for homogeneity was used with the goal of identifying significant differences between the services and membership types. (This test is a variation of the Cramer-von Mises test). Basically tests whether two circular distributions, such as these temporal patterns, differ significantly from one another. Hypothesis is that temporal patterns come from the same population—in this case that is rejected for member bikeshare and scooter, accepted for member v casual bikeshare and casual bikeshare v scooter, suggesting these pairs are more similar.  -CosSim again used to determine degree of similarity between casual, member, and scooter  -To compare scooter and bikeshare spatial activity similarity, Voronoi polygon tessellations were created for bikeshare stations, and all scooter trip starts/ends were assigned to a polygon. Did trip density maps in the same way subtracting one service from the other  -Earth Mover’s Distance – calculates similarity between two multi-dimensional matrices by computing the cost of converting one distribution into the other.  -CosSim of time distributions between services by polygon are also mapped to identify highest similarity and lowest similarity areas  -note that limitation because CosSim decreases as the sparsity of trips increases | -Temporal usage distribution – start time and end time distributions are nearly identical bc average trip duration is about 5 minutes  -Tues-Thurs most similar, Sat-Sun second most similar. Least similar is between weekend and midweek days.  -Weekday and weekend trips are both non-spatially random, higher degree of spatial clustering on weekdays than weekends. Weekday trips more centered in the downtown core relative to weekend trips with greater spatial dispersion  -weekday trips dominate the majority of TAZs  -Bikeshare members are more peak-y than casual bikeshare users  -Casual v member bikeshare users are more similar than casual v scooter, which are more similar than the proven dissimilar member v scooter  -Member bikeshare trips dominate downtown core, scooter share broader regional adoption outside of downtown core, casual bikeshare dominates along waterfront (suggesting recreational use)  -Highest level of spatial similarity is also member v casual bikeshare. Least similar spatial distribution is casual v scooters.  -future discussion could involve: equity analysis on regions served, variation of different scooter share services, five minute timeframes might be too high, better analysis of land use by density, impact of climate, seasonal changes, hyper-local weather should be assessed, results should also be compared to existing modes of transportation (ie car, ride-hailing, public transit) |
| Do e-scooters fill mobility gaps and promote equity before and during COVID-19? A spatiotemporal analysis using open big data  Washington DC | -Washington DC API provides vehicle info in GBFS data (one minute time interval scraping), GTFS data from transit authority, bikeshare data from Capital Bikeshare  -all e-scooters providers considered when evaluating supply of scooter, only static ID scooter providers used when examining trips  -excluded scooter trips shorter than 0.02 miles or longer than 10 miles, shorter than 5 minutes or longer than 90 minutes, or average travel speed above 20 mph  -for pre-covid looked at July 15-21 2019, for covid period looked at June 15-21 2020  -For service supply, looked at 7 am, 12 pm, 5 pm, 8 pm  -spatial distribution of e-scooters and bikesharing at these times  -supply of transit services by number of vehicles passing stop for the following hour  -kernal density used – value of access to the mode decreases with distance, terminating at 0.25 miles for transit stops, 0.125 miles for bikeshare, 0.05125 miles for scooters. Also weighted by population- # of vehicles for transit, # of available bikes for bikesharing stations, 1 for e-scooters (does this make sense? Longer wait times could be weighted more unfavorably)  (maps created, spatial distribution compared visually)  -Correlation analysis used to evaluate similarity of spatial distributions of supply intensity (coefficient closer to 1 = stronger competitive, closer to 0 – stronger collaborative)  -for trip O/D comparison, first classified whether or not e-scooter trips’ O/D fell into the service area of transit or bikesharing stations. second, identified likely combined e-scooter and transit trips by examining if scooter starts or ends at a transit stop  -did e-scooter trip end within or outside transit coverage area? (0.25 mile radius, ArcGIS Network Analyst to generate service area within 5 min walk)  -Chart, diagram  Description automatically generated  -also compared with bikeshare (0.125 mile radius), only three trip types (competing with bikeshare is 1&2, extending service area is 3, covering uncovered service area is 4)  -analyzed complementary e-scooter/transit trips by IDing if scooter starts or ends within distance of rail entrances (only rail chosen bc of past literature suggesting bikeshare/rail linkage). Used a lower bound 30 ft estimate and upper bound 100 ft estimate to get range of potential parking distances  -for analysis of travel time differences using transit v using scooters (ie trip 1 v trip 2)  -exclude leisure trips (travel speed lower than 8 mph, distance under a quarter mile, or happening at tourist sites such as National Mall)  -generate fastest transit alternative for each e-scooter trip using ArcGIS Pro Network Analyst tool (network based on GTFS data) – includes walking time, waiting time, boarding/alighting time (set to 30 seconds), in-vehicle travel time, time required for transfers if necessary (does this for user-specified date and departure time, in this case the e-scooter O)  -get median transit travel times for every minute of the 10 minutes before and after the start time of the e-scooter trip (assumes people will adjust their schedule slightly to minimize wait time)  -estimated travel cost for scooter trips and comparable transit trips (only fare considered) | -Spatial distribution of e-scooters similar to that of bikesharing except for two noticeable differences (scooters concentracted around downtown and capitol areas, and are accessible to a wider geographic area than bikesharing)  -Scooters don’t appear to expand the service area of public transit (could potentially look at time of day differences here though)  -transit supply more evenly distributed than other two (less market-driven)  -Spatial patterns largely similar for pre-Covid and during-Covid, however transit supply smaller during covid  -Bikesharing and escooters greatest competition, moderate competition (0.45-0.61) with transit  -more e-scooters and bikeshare trips end at central locations than start from these locations (concentrates supply, more rebalancing efforts required throughout the day)  -more complementarity between modes during covid  -90% of scooter trips have O/D in transit stop service areas, 5% D outside service area, almost 0 O/D outside  -number and proportion of scooter trips connecting to rail transit declined significantly (8-12% to 6-7%) during covid, also was less peaky  -median scooter trip lengths increased slightly in distance and duration  -transit travel times on average 4.7 minutes longer than e-scooter trips before covid, decreased to 2.5 min during covid (likely due to reduced congestion)  -further discussion: places with less robust public transport system? E-scooter service difference across population groups. Traveler preference and behavior (modal shift), conditions where people more likely to use e-scooter complementary with transit unexplored. Small data approaches (focus groups, surveys, interviews) could be integrated into big data approaches |
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