

Faster and Cheaper: How Ride-Sourcing Fills a Gap in Low-Income Los Angeles Neighborhoods

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EXECUTIVE SUMMARY

Ride-sourcing services such as Uber and Lyft have created unprecedented competition for the taxi industry and sparked intense debate between detractors and proponents of the new services. To date, the arguments have been



The findings demonstrate that compared to taxis, Uber is faster and cheaper by a large measure.

based on emotion and self-interest rather than evidence. Funded by Uber Technologies, Inc., BOTEC designed and ran a rigorously controlled study in order to generate actual data as to the relative performance of taxis vs. UberX rides in low-income Los Angeles neighborhoods. The findings demonstrate that compared to taxis, Uber is faster and cheaper by a large measure. Data collected in this study shows that an app-summoned UberX ride arrives in less than half the time of a telephone-dispatched taxi and costs less than half as much, even during periods of “surge pricing.” UberX was also more reliable, with no wait time exceeding 30 minutes.

BACKGROUND

Millions of low-income households do not have an automobile. In sprawled cities like Los Angeles where cheap, reliable, point-to-point transportation is critically needed, public transit is not always a complete solution.¹ Taxi services help fill this gap, but telephone-dispatched taxi service in poor urban neighborhoods is consistently slower and less reliable than taxi service in wealthier communities.² Ride-sourcing providers such as Uber promote their services as a low-cost complement to public transit throughout Los Angeles.³

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1. Tomer (2011)
 2. Frankena and Pautler (1986); Hara Associates Inc. (2013); and Nygaard (2013).
 3. Uber Technologies, Inc. (2015).

Taxi companies argue that Uber disadvantages low-income and disabled individuals, as unregulated Uber drivers choose to only provide services in wealthy areas where passengers can pay higher fares and are easier to transport.⁴

The current study evaluates quality differences between dispatch-called taxis rides and app-summoned UberX rides in low-income areas in Los Angeles, measuring three aspects of service quality: (1) average wait times, (2) reliability (measured by variability in wait times and the prevalence of very long waits), and (3) cost-per-ride.

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4. Maddaus (2015).

METHODS

Los Angeles was selected as a good proxy for most U.S. urban areas where residents have historically relied on telephone-dispatched taxis, but now have the option of using a ride-sourcing service. The study restricted data collection to low-income areas, defined as those in which the average household income is below \$50,000 per year for a family of three.⁵ Those neighborhoods constituted the possible experimental “universe.” We chose the neighborhoods to be studied based on receptiveness to the study by the management of the establishments used as pick-up and drop-off locations (cafés, parks, and churches, etc.), and for safety of the study participants.

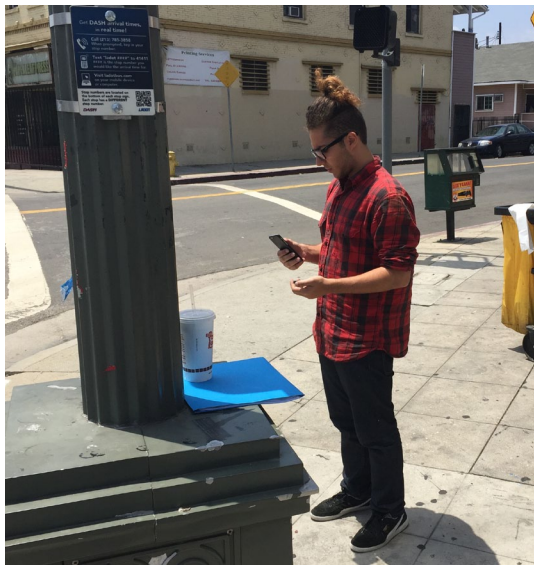
On each study day, riders were deployed to a specific observation area where they traveled through the observation area in pairs, alternating use of UberX and taxi service. All riders traveled

along predetermined routes to fixed locations manned by a “location leader” who checked on them and monitored their progress.

The experimental design employed a “drag race” approach to allow direct comparisons of cost-per-ride and driver response time at similar times of day and under similar circumstances. Both riders in each pair requested transportation simultaneously from the same location: one summoned an UberX and the other called for a taxi. Upon arrival at their destination, the riders checked in with their “location leader” and waited for five minutes to allow the UberX or taxi to travel away from the location before initiating the call for a ride to the next location. At each stop on the course, paired riders switched modes of travel; the rider who used UberX on one trip used a taxi for the next and vice versa. Prior to beginning the course, riders were given a list of companies to call for their taxi rides. The list was randomly generated from the group of licensed taxi companies listed as serving the geographic region of the observation area.⁶

Throughout the course, the riders collected two measures of wait time: “request time” and “total wait time.” For UberX, “request time” was measured starting when riders took their smart phones out of their pockets and ending when the Uber app reported “driver en route.” For taxis, it was measured starting when riders took their smart phones out of their pockets to dial the taxi operator and ending when the dispatcher informed the rider the taxi was on the way. For “total wait time,” the riders kept the stopwatches running and noted the total time elapsing between taking their smart phones out to call or summon a ride and

5. This definition of “low-income” comes from the Los Angeles Housing Authority (income less than 80% of the area’s median), assuming a household of three persons as the average household size in Los Angeles County is 3.01 (United States Census Bureau, 2009-2013). Neighborhoods were defined according to Mapping LA from the Los Angeles Times.



6. Taxi company service areas were determined from http://www.taxicabsla.org/areas_served.html.

getting into the UberX or taxi. “Response time” was later calculated by subtracting “request time” from “total wait time.” The study’s primary results compare “total wait time” between UberX and taxi service; Appendix B provides comparisons of “response time” and “request time” separately.

In addition to wait times, riders recorded the cost of each trip. For taxi travel, riders paid cash and directly recorded the total cost of their trip (fare plus tip). For UberX, cost-per-ride was obtained by using an Uber feature known as “Uber for Business,” which is designed for expense accounting. Instead of having the riders copy down the information, we were able to take it directly from the Uber records.

Unlike taxis, UberX uses “surge pricing,” raising rates when the supply of drivers is scarce relative to demand for rides. Riders in the experiment were instructed to summon UberX regardless of whether surge prices were in effect, and the reported cost figures include rides (roughly one-sixth of the total rides) during a period of surge pricing.

To prevent bias caused by driver preference for long (and therefore more profitable) trips, riders did not disclose their destination to the taxi service or to UberX. Taxi dispatchers are prohibited from asking for a customer’s destination, so riders did not provide their destination when calling for a taxi.⁷ Although an UberX rider can enter the destination when summoning the ride, the UberX driver does not see the destination until the ride begins.

From the pool of Los Angeles communities that satisfied the income criteria set by the evaluation design (see Appendix D), neighborhood clusters were selected to provide a broad representation



of low-income areas. The study began in North Los Angeles (the Valley) followed by South, Central, and East Los Angeles. Van Nuys was arbitrarily selected as the initial observation area.⁸ For this first day of observation and data collection (Friday, May 8, 2015) seven stops were selected for the course, and 18 riders traveled their routes from 10:30 a.m. until 7 p.m. (with a half-hour break midday). Appendix Figures D1.1 and D1.2 show the boundaries of the Van Nuys observation area, which included some surrounding areas such as Valley Glen. Appendix Table D1 reports income and crime statistics for these neighborhoods.

DESCRIPTION OF RIDERS

To commence the study, we hired an ethnically diverse group of 18 riders from a local temporary staffing agency and provided them with stopwatches and a back-up phone battery to recharge their phones if needed.⁹ We held a three-hour training at a hotel banquet room in Van Nuys the evening before Day 1 of the study. The identity of the funder (Uber Technologies) was not disclosed to the riders,

7. See Rule 213 of “Taxicab Rules and Regulations of the Board of Taxicab Commissioners.” (http://ladot.lacity.org/stellent/groups/departments/@ladot_contributor/documents/contributor_web_content/lacityp_029021.pdf).

8. Subsequent neighborhoods were selected through a process of complete randomization. The randomization provided coverage of neighborhoods in North, Central, and East LA; however no areas in South Los Angeles were selected.

9. Ethnicity of the rider was not recorded as a variable in the study.

and we impressed upon them the importance of not telling the UberX or taxi drivers that they were participating in a study. Riders were meticulously instructed about how to measure time intervals using stopwatches, and how to complete the survey. Study managers ensured that riders understood the support available from headquarters, team captains, and location leaders as well as their responsibility to stay in constant contact with their location leaders posted at each stop. Each rider was provided with cash to pay taxis. The UberX rides were set up for payment through the “Uber For Business” account so the rider was not charged.

DESCRIPTION OF SURVEY

Every rider completed a digital survey for each ride taken. The electronic version was transmitted to a spreadsheet that was monitored in real time to ensure completeness and accuracy. Responses that were outside of the range of possible values (e.g. response times of zero or request times of several hours) were immediately followed up with a call, and riders were asked to check the response, verify accuracy, and if needed, correct the entry. Any observations reflecting data-entry errors were dropped from the study. These observations have been preserved in the dataset as “dropped observations.” Overall, five time measurements and one cost measurement were dropped.

The following are the questions and their accompanying instructions from the electronic Google Forms survey as they appeared to the riders:

Rider ID—(First four letters of first name and last initial (for example: PeteG.)

Starting Point—(Give address close to this location’s address, but not the exact address. Stay within sight of location leader.)

Destination—(Give address and intersection for destination.)

Mode of Travel—(example for Van Nuys observation area)

- UberX
- United Taxi of San Fernando Valley
- City Cab

How long did it take for you to successfully request a ride?—(As measured from the time the phone is in your hand to the time the Uber app or dispatcher confirms that a ride is on the way. This is the first split time recorded.)

Approximately what time did you begin hailing the ride?—(Check the time right before you summon the ride and record it.)

How long did it take from beginning your watch to the car arriving and you getting to the door?—(This will be your second split time measured from the time you started the stop watch to the door. Hit the stop to record this.)

Taxi License Number—(This will be a three or four digit number on the inside of the rear passenger door.)

How much did your ride cost? (Taxi Only)—(Include tip for taxi’s and state number in dollars and cents (e.g. 12.00, 10.00, etc.)¹⁰

Driver Attitude (2 is Neutral.)

Number of times you had a ride cancel, were placed on hold, got a busy signal, or were disconnected—(If any of these happened, add them up. Then in the comments, explain what happened.)

Comments—(optional)

Survey responses were submitted directly into the data collection system via a link from Google Forms accessed from the rider’s

10. Tipping protocol was set at approximately 15%. Riders paid for taxis with cash and were asked to pay in rounded dollar amounts so they did not have to work with coins. If the percentage was close to 50 cents over a dollar amount including tip riders were asked to round up and pay that amount.

smartphone. The survey link was provided by the research data collection team. The riders were instructed to complete the answers to the best of their ability and were made aware of the importance of submitting accurate responses.

PROCEDURES FOR ANALYZING THE DATA

At headquarters, the responses from live-streamed Google Forms were monitored for accuracy. The form permitted riders to edit



their responses, in which case the entry would be flagged with an indicator for the edited field. Google Forms data were regularly backed up to local copies of Excel spreadsheets. Once these data were thoroughly reviewed, a data analyst checked and cleaned them.¹¹ This cleaned raw data set was then given to a statistician who reviewed it to confirm appropriate reporting, questioned the crew in Los Angeles as needed, and gave final approval to these raw data. The final raw data sheets were submitted to Uber Technologies a week after completion of the project.

Microsoft Excel was used to compute summary statistics and confidence intervals based on t-tests for two samples, assuming unequal variances. G*Power was used to compute effect sizes. For all measures of interest, effect-size computations and results are provided in Appendix C.

11. A handful of invalid entries (e.g. zero request/arrival times) were removed. Including these entries does not qualitatively change the results. The data analyst was only blinded as to service provider on the second day of validation runs (6/6/2015), Non-blinded and blinded analytics yielded similar results. See text for details.

INITIAL RESULTS

From Day 1 in Van Nuys, the average total wait time (from initiating ride request until driver arrival for pick-up) for UberX was 7 minutes and 42 seconds ($n=56$; $SD=5$ minutes, 15 seconds) and the average taxi response time was 18 minutes and 45 seconds ($n=55$; $SD=20$ minutes, 29 seconds). On average, the time elapsed from taxi ride dispatch until taxi ride arrival was 11 minutes and 3 seconds (2.4 times) longer than that for UberX. This difference is highly statistically significant ($p<0.001$).¹²

To ensure that the results were not driven by a few extreme observations, average wait times were recalculated excluding outliers.¹³ Dropping the three taxi wait times that qualified as outliers—no UberX observations met the criteria—reduces the mean taxi total wait time to 12 minutes and 30 seconds, which is still twice the UberX mean.

On average, taxis cost more than twice as much as UberX.

The cost-per-ride differences were also substantial. The mean cost of an UberX ride was \$7.26 ($n=57$; $SD=\$1.42$). The mean cost for a taxi ride was \$17.09 ($n=50$; $SD=\$3.21$).¹⁴ On average, taxis cost more than twice as much as UberX; this difference is highly statistically significant ($p<0.001$).¹⁵

12. The corresponding 95% confidence interval for the difference in response times (taxi vs. UberX) ranges from 5 minutes, 21 seconds to 16 minutes, 45 seconds.

13. Outliers were defined using Tukey's method of leveraging the interquartile range (IQR), removing extreme outliers more than $3 \times IQR$ below the first quartile or $3 \times IQR$ above the third quartile (Tukey, 1977).

14. The discrepancy in number of observations between the time data and the cost data is due to a few errors where respondents failed to enter data in one of the fields.

15. The corresponding 95% confidence interval for the cost data from Day 1 ranges from \$8.85 to \$10.82.

Given the magnitude of the differences observed on Day 1, a full-scale continuation of the experiment seemed unnecessary. However, adjustments to the original experimental design were implemented in follow-up field studies to address the following potential threats to validity:

- 1) **Internal validity:** Due to the high volume of rides generated by the experiment, our results may reflect differential learning of one group that is solely a function of the experiment. Through the course of the initial experiment in Van Nuys, we had obtained anecdotal evidence from the riders that some taxis—but no UberXs—were waiting in areas that had become “hot spots” because of the study. If radio communication between taxi drivers allowed them to more quickly recognize that multiple trips were being requested from the same locations, our results would be biased in favor of taxi response times. Conversely, if the atypical volume of rides more rapidly exhausted the taxi company's system capacity compared to UberX (for example, if the unpredicted spike in demand led to delays by dispatchers in assigning the call to a driver), the increased density of ridership could have disadvantaged taxi response times.
- 2) **External validity:** The Van Nuys region may not be representative of other low-income areas in Los Angeles since taxi service in Van Nuys is zoned under a region of large area and low demand. Van Nuys is in Zone A of the LA Taxicab Commission's service zones, which constitutes 47% of the total city area but only 15% of the population and 16% of taxi service demand.¹⁶ We were also

16. Board of Taxicab Commissioners (2015)

concerned that the study could have overloaded the area; the high demand generated by the experiment might not have been representative of typical taxi service, as the taxi distribution system in place in Van Nuys places a fixed number of drivers for a territory on any given shift, presumably based on experience of lower demand. We also decided that it was important to study response times and cost-per-ride on other days of the week.

- 3) **Experimenter bias:** Since the funder, Uber Technologies, had been aware of the time and place of the initial field study in and around Van Nuys, an argument could be made that the client, its proxies, or the hired researchers themselves had intentionally or inadvertently affected the results. While the funding client's policy division is separate from the operations division, a different experimental design would mitigate any concerns about potential interference.

To address these concerns, validation rounds for the experiment were conducted in other areas of Los Angeles, with very small rider groups to reduce any potential impact on the transportation "ecosystems" and to provide greater generalizability. Uber Technologies was not informed of any of the locations used for the follow-up studies. Given the large differences seen in the initial experiment, smaller sample sizes were deemed sufficient for the validation rounds.



VALIDATION ROUNDS

In planning for the validation rounds, we compiled a list of neighborhoods satisfying the original income threshold of \$50,000 per year for the average household of three. From that list, a random number generator was used to select 21 neighborhoods in Los Angeles to serve as the epicenters for the riders to collect observations in the validation rounds.

For the safety of the riders and researchers, we excluded areas with a rate of violent crime that was more than one third higher than that of the previously studied Van Nuys area (25.8 violent crimes per 10,000 people in a six-month period). At the time of the study, Van Nuys was ranked 54th most violent out of the 272 Los Angeles neighborhoods.¹⁷ For future rounds, neighborhoods with rates below 35 violent crimes per 10,000 people deemed to be adequately safe for the riders. This eliminated the 35 (12.9%) most violent neighborhoods from study activity (see Appendix Table D2). This corresponds to the removal of 54.6% of the low-income neighborhoods that composed the experimental universe, leaving 29 neighborhoods from which the validation round observation areas were randomly chosen (see Appendix Table D1).

The randomly selected neighborhoods were (1) Larchmont, whose observation area became Larchmont/Koreatown/Echo Park, (2) Cypress Park, whose observation area became Cypress Park/Elysian Valley/Lincoln Heights, and (3) Panorama City, whose observation area became Panorama City/Valley Glen/North Hollywood. In order to avoid the internal validity problem described above (concern that the study itself could affect the results), small groups of four

riders or fewer traveled in any given observation area. Three researchers rode the new routes with riders recruited from a staffing agency. Each researcher and his partner worked in distinct areas.

In each of these observation areas, 30 locations with publicly accessible addresses (parks, shops, schools, libraries, etc.) were chosen from Google Maps and Google Earth as pick-up and drop-off locations. The locations were fairly evenly distributed inside of a shape-file area that represented the central neighborhood and adjacent poor but lower-crime neighborhoods (see Appendix D). Those 30 locations were entered into a spreadsheet and a random generator was used to select 21 possible locations.¹⁸ From this random subset of 21 locations, a configuration of 12 drop-off and pick-locations was designated to ensure consistent and reasonably priced ride distances and course flow.

On Thursday, May 28, 2015, the three researchers planned to meet their “buddies” from the staffing agency but only one of the three temporary employees showed up for the shift. Thus, two of the researchers rode the Larchmont and Cypress Park routes alone, while the third rode in the initial “drag race” fashion with a staffing-company rider in the Panorama City route. For the first ride, the paired riders were randomly assigned to UberX or taxi by a coin toss.

The riders completed the experiment, collecting 24 taxi observations and 27 UberX

17. Violent Crime for Los Angeles from the Los Angeles Times <http://maps.latimes.com/neighborhoods/violent-crime/neighborhood/list/>

18. The locations were written into rows on a spreadsheet. In the column next to the names of the locations a random number was placed from the Excel random number generator. These rows were then sorted from lowest to highest random number and the top 21 were selected.



observations.¹⁹ Response times and cost-per-ride differences yielded results similar to those from Van Nuys.

The next round of validation (the third day of study) took place on Saturday, June 6, 2015; on this day, two pairs of riders from the first day of study (5/8/2015) ran the Larchmont and Cypress Park courses. For this day of observation, data collection was double-blinded. Specifically, experimental data were collected by one statistician who replaced the identifiers “UberX” or “Taxi” with the numerals “1” or “2” before sending the data to another analyst who ran the calculations on wait time and cost-per-ride. The identifiers were revealed only after the final computations were completed. Again, the results demonstrated a clear difference between wait times and cost-per-ride in all the low-income neighborhoods studied.

- On average, a taxi takes two to three times longer to arrive than an UberX.
- On average, a taxi costs more than twice as much as an UberX.

A final round of validation was necessary to compare cost-per-ride in study environments where previously only one mode of transportation

19. For time data, there are measurements for 25 taxi and 27 Uber rides; in cost data, there are figures for 23 taxi and 23 Uber rides. The discrepancy is due to dropped observations from the cost data where when only one mode of transportation was taken from one location to the next, so there is no comparison data.

had been taken from one location to the next. On the final round of validation, Thursday, June 25, 2015, two researchers from the team went to specific stops along the route in the Cypress Park/Elysian Valley/Lincoln Heights area to collect observations. The findings are limited due to the small sample size, but observations on this day were consistent with—even somewhat more pronounced than—those on the three previous days.

On average, a taxi costs more than twice as much as an UberX.

RESULTS FOR VALIDATION DAYS (STUDY DAYS 2, 3, AND 4)

On the second study day, (5/28/2015) the average UberX total wait time was 7 minutes and 24 seconds ($n=27$; $SD=5$ minutes, 7 seconds) and the average taxi wait time was 21 minutes and 29 seconds ($n=25$; $SD=13$ minutes, 33 seconds). This difference is highly statistically significant ($p<0.001$). Similarly, on the third study day, (6/6/2015) the average UberX response time was 5 minutes and 50 seconds ($n=21$; $SD = 4$ minutes, 7 seconds) while the average taxi wait time was 19 minutes and 30 seconds ($n=20$; $SD=14$ minutes, 47 seconds). This difference is also highly statistically significant ($p<0.001$).²⁰ Finally, on the fourth day of the study, (6/25/2015) the average UberX wait time was 5 minutes and 58 seconds ($n=4$; $SD=2$ minutes, 18 seconds) while the average taxi wait time was 28 minutes and 57 seconds ($n=4$; $SD=17$ minutes, 10 seconds). Due to the small number of observations, the difference of 22 minutes and 1 second is statistically significant only at the 10% level ($p=0.08$).

20. The 95% confidence interval for the difference in response times ranges from 8 minutes, 11 seconds to 19 minutes, 58 seconds for Day 2; it ranges from 6 minutes, 34 seconds to 20 minutes, 46 seconds for Day 3.

Results for the difference in cost-per-ride were similar for all validation days. On the second study day, the mean cost of an UberX ride was \$5.28 (n=23; SD=\$1.70) while the mean cost for a taxi ride was \$12.04 (n=23; SD=\$2.69). On the third study day, the mean cost of an UberX ride was \$5.47 (n=19; SD=\$1.45) while the mean cost for a taxi ride was \$12.47 (n=17; SD=\$3.24). Finally, on the fourth study day, the mean cost of an UberX ride was \$5.04 (n=4;

SD=\$0.77) while the mean cost for a taxi ride was \$11.69 (n=3; SD=\$2.31). For all days, these differences are statistically significant at the 5% level ($p < 0.001$ for Days 2 and 3; $p = 0.02$ for Day 4).²¹

21. The 95% confidence interval for the difference in costs is [5.42, 8.11] for Day 2, [5.23, 8.77] for Day 3, and [0.69, 12.62] for Day 4.

FINAL RESULTS

Tables 1 and 2 show summary statistics for the data collected from all rounds of the experiment combined. To give less weight to extreme values, outlying observations have been removed.²²

From Table 1, total wait times were substantially shorter for UberX. The mean wait time for

UberX was 6 minutes and 49 seconds (n=106; SD=4 minutes, 8 seconds). The mean wait time for taxi service was 17 minutes and 42 seconds (n=101; SD=11 minutes, 44 seconds). On average, the arrival wait time for taxis was 10 minutes and 53 seconds (2.6 times) longer than that for UberX. This difference is highly statistically significant (p<0.001).²³

22. See Footnote 6. For wait times, 2 outlier UberX observations and 3 outlier taxi observations were removed. For cost-per-ride data, only 1 outlier taxi observation was removed.

23. The corresponding 95% confidence interval for the difference in response times ranges from 8 minutes, 26 seconds to 13 minutes, 19 seconds.

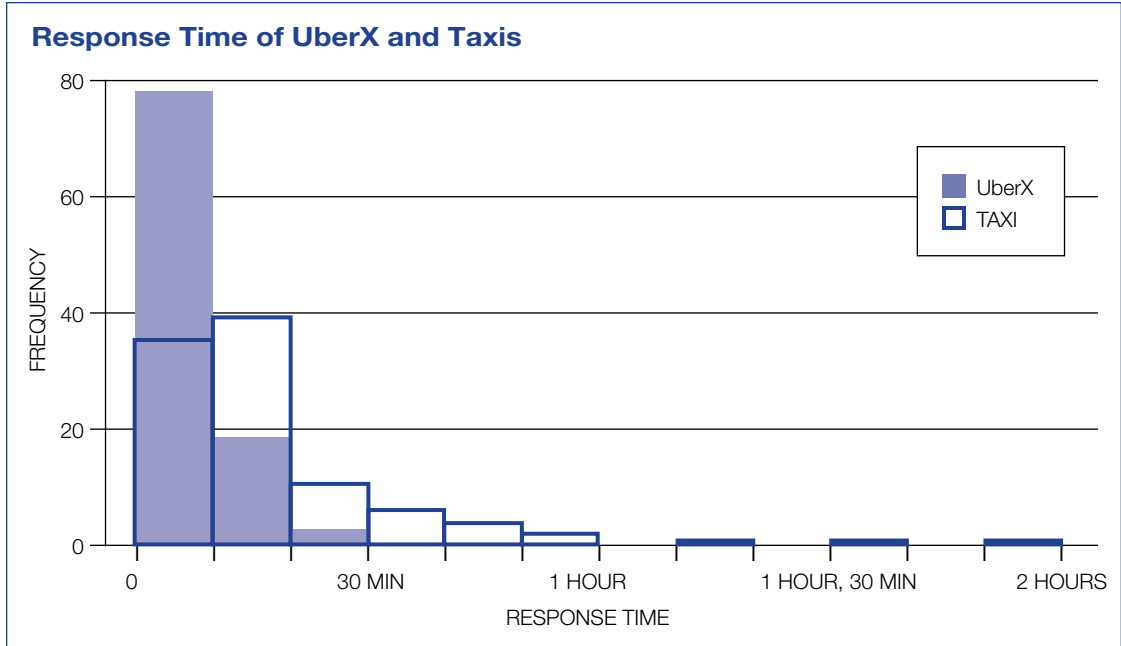
Table 1: Total Wait Time Summary Statistics (hrs:min:sec) for All Days

	Obs	Mean	Median	Std Deviation	Min	Max
UberX	106	6:49	5:52	4:08	1:07	20:00
Taxi	101	17:42	14:33	11:44	4:24	57:00

Notes: Outlying observations were excluded. Outliers were determined by calculating the quartiles and inter-quartile range (IQR) of the total wait time. To determine the cutoff above which observations were dropped as extreme outliers ("upper fence"), the IQR was multiplied by 3 and added to the third quartile. To determine the cutoff below which observations were dropped as extreme outliers ("lower fence"), the IQR was multiplied by 3 and subtracted from the first quartile. In all, three taxi and two UberX observations were dropped as outliers.

The figure below shows a distribution of the overall wait times for UberX and taxis. Taxis have a wider spread of wait times; while most wait times were less than 20 minutes,

a significant number of wait times exceeded 30 minutes whereas UberX response times were tightly concentrated in the 0 to 10 minute range.



Excluding outliers, the figure below shows a similar spread pattern of UberX and taxi wait times. Taxi wait times are greatly spread across

a one-hour time frame whereas UberX wait times are primarily below 15 minutes with very few observations exceeding that time frame.

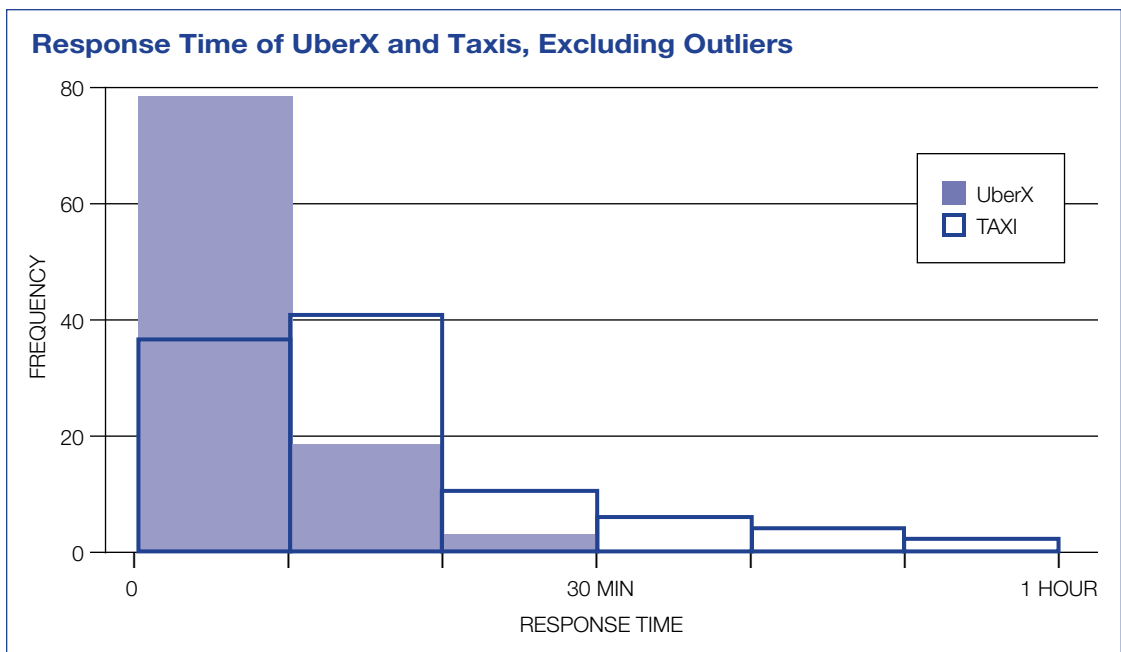


Table 2 shows that the difference in cost per ride was equally pronounced. The average UberX ride cost \$6.40 (n=103; SD= \$1.75), and the average taxi ride cost \$14.63 (n=92; SD=\$3.43). Again, the mean difference in costs of \$8.23 (taxi rides costing 2.3 times that of UberX) between taxi and UberX is highly statistically significant (p<0.001).²⁴

Of all UberX observations over the course of the study, 17.6% (19 of 108) took place during “surge pricing.” Perhaps surprisingly, these did not occur disproportionately during rush hours. For example, on Friday, May 8, 2015, after 3:00 p.m. (the traditional evening rush hour in Los Angeles), 11.6% (5 of 43) of the rides were surge-priced. Even during surge periods, UberX fares remained below taxi fares on the same routes.

24. The corresponding 95% confidence interval for the difference in costs ranges from \$7.44 to \$9.01.

Table 2: Cost-per-Ride Summary Statistics (\$) for All Days

	Obs	Mean	Median	Std Deviation	Min	Max
UberX	103	6.40	6.28	1.75	4.00	11.68
Taxi	92	14.63	15.00	3.43	8.00	22.00

Notes: Outlying observations were excluded. Outliers were determined by calculating the quartiles and inter-quartile range (IQR) of the total wait time. To determine the cutoff above which observations were dropped as extreme outliers (“upper fence”), the IQR was multiplied by 3 and added to the third quartile. To determine the cutoff below which observations were dropped as extreme outliers (“lower fence”), the IQR was multiplied by 3 and subtracted from the first quartile. In all, only one taxi observation was dropped as an outlier.

LIMITATIONS

Concerns for worker safety limited the scope of our study. A substantial number of low-income Los Angeles neighborhoods were excluded from study due to high rates of violent crime, and we collected observations only during daylight hours. These factors limit the generalizability of our findings, as real-life usage of taxi and UberX services would likely occur during night hours and in high-crime areas. Unlike regulated taxis, UberX drivers are not required to provide service within a designated zone, and thus UberX drivers may choose not to work in areas that are considered poor or dangerous during late hours. This study did not capture any potential exercise of discretion by UberX drivers that could affect nighttime service response decisions. This is an important limitation that warrants further exploration.

Additionally, Los Angeles may not be representative of other low-income urban areas in the United States. Los Angeles has a specific set of territories, rules and regulations for taxi service that may differ from those of other higher density cities. Prevalence of telephone dispatch is another potential difference between Los Angeles and other densely populated urban markets: given the sprawl of

Los Angeles, taxi drivers typically don't cruise for passengers. Phone dispatch is customary and largely necessary to summon a taxi, though a transition to smart phone app technology for taxis is currently underway. These regulatory restrictions may be a cause of slow response times for taxis in Los Angeles; indeed, throughout the course of the experiment, there were occasions when a rider would get passed from one taxi provider to another as the initial company did not have adequate drivers available in a given territory. Other cities' regulatory structures may have more fluidity between service areas that would allow for faster taxi response times. Studies are needed in low-income areas of other major cities and non-urban low-income markets to determine how well these results generalize.

Another potential limitation is that using Uber—unlike taking a taxi—requires a smart phone and a credit/debit card or PayPal account. A 2015 Pew study found that 71% of Americans with incomes under \$50,000 own a smart phone,²⁵ but some of the poorest people who could benefit most from cost savings in transportation do not have the two prerequisites for Uber travel.

Finally, response times and transportation costs are not the only measures of ride service quality. Other factors include passenger safety, driver competency and familiarity with the neighborhood, driver personality, certainty about ride dispatch and likely arrival time, equal treatment of riders regardless of sex, race, disability or perceived socioeconomic status, and vehicle cleanliness. The current study did not attempt to measure those characteristics.



25. Pew Research Center (2015)

CONCLUSION

This study reveals a pronounced difference in response time and cost per ride between taxi and UberX ride service provision in low-income areas of Los Angeles. On average, these riders could expect to wait twice as long and pay twice as much for a taxi as for an UberX ride. These differences are substantial for individuals with limited incomes.

Though the results for this study are striking, the study should be replicated in other cities and in lower-income areas, including high-crime areas, in order to establish how far these findings are generalizable. We would be happy to share our methods and data for replication and re-analysis.



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APPENDIX A: RESULTS SEPARATED BY DAY

Table A1.1: Total Wait Time Statistics (hrs:min:sec) for Day 1

VAN NUYS CLUSTER—FRIDAY 5/8/15

	Obs	Mean	Median	Std Deviation	Min	Max
UberX	56	7:42	6:20	5:15	1:07	27:33
Taxi	55	18:45	13:29	20:29	4:24	1:59:24

Table A1.2: Cost of Ride Statistics (\$) for Day 1

VAN NUYS CLUSTER—FRIDAY 5/8/15

	Obs	Mean	Median	Std Deviation	Min	Max
UberX	57	7.26	6.90	1.42	4.00	11.62
Taxi	50	17.09	17.00	3.21	10.00	33.00

Table A2.1: Total Wait Time Statistics (hrs:min:sec) for Day 2

MULTIPLE OBSERVATION AREAS—THURSDAY 5/28/2015

	Obs	Mean	Median	Std Deviation	Min	Max
UberX	27	7:24	5:53	5:07	1:31	26:53
Taxi	25	21:29	16:41	13:33	6:51	46:10

Table A2.2: Cost-per-Ride Statistics (\$) for Day 2

MULTIPLE OBSERVATION AREAS—THURSDAY 5/28/2015

	Obs	Mean	Median	Std Deviation	Min	Max
UberX	23	5.28	4.68	1.70	4.00	11.68
Taxi	23	12.04	11.00	2.68	8.00	19.00

Table A3.1: Total Wait Time Statistics (hrs:min:sec) for Day 3

MULTIPLE OBSERVATION AREAS—SATURDAY 6/6/2015

	Obs	Mean	Median	Std Deviation	Min	Max
Uber	21	5:50	4:14	4:07	2:00	16:31
Taxi	20	19:30	14:58	14:47	7:15	57:00

Table A3.2: Cost-per-Ride Statistics (\$) for Day 3

MULTIPLE OBSERVATION AREAS—SATURDAY 6/6/2015

	Obs	Mean	Median	Std Deviation	Min	Max
UberX	19	5.47	5.16	1.45	4.00	9.67
Taxi	17	12.47	12.00	3.24	8.00	19.00

Table A4.1: Total Wait Time Statistics (hrs:min:sec) for Day 4

MULTIPLE OBSERVATION AREAS—THURSDAY 6/25/2015

	Obs	Mean	Median	Std Deviation	Min	Max
UberX	4	5:58	6:13	2:18	3:24	8:03
Taxi	4	28:57	31:46	17:10	7:17	45:00

Table A4.2: Cost-per-Ride Statistics (\$) for Day 4

MULTIPLE OBSERVATION AREAS—THURSDAY 6/25/2015

	Obs	Mean	Median	Std Deviation	Min	Max
UberX	4	5.04	5.13	0.77	4.08	5.80
Taxi	3	11.69	10.75	2.31	10.00	14.32

APPENDIX B: REQUEST AND RESPONSE TIMES SEPARATELY FOR ALL DAYS

Table B1.1: Request Time Summary Statistics (hrs:min:sec) for All Days

	Obs	Mean	Median	Std Deviation	Min	Max
UberX	106	1:09	0:48	1:32	0:05	12:00
Taxi	101	2:16	1:37	3:55	0:36	40:00

Notes: "Request time" is time from request initiation until service dispatch. Outlying observations for "total wait time" were excluded. See Table 1 on page 15 for details.

Table B1.2: Response Time Summary Statistics (hrs:min:sec) for All Days

	Obs	Mean	Median	Std Deviation	Min	Max
Uber	106	5:40	4:51	3:35	0:43	16:23
Taxi	101	15:26	12:15	11:28	0:34	55:33

Notes: "Response time" is time from service dispatch until ride arrival. Outlying observations for "total wait time" were excluded. See Table 1 on page 15 for details.

APPENDIX C: EFFECT-SIZE CALCULATIONS

At the planning stage for the experiment, a sample size “n” of 1212 was set in order to allow detection of a 0.15 effect size with 90% confidence and 80% power. This “n” was calculated by determining a base of 1102 observations necessary, and then adding a standard attrition buffer of 10%. To calculate the necessary sample size, research team statisticians used G*Power; sample size calculations

were based on a two-tailed t-test for the difference between two independent means (two groups: UberX and taxi) and a policy standard of 90% confidence and 80% power to detect a 15% effect size.

Effect sizes were calculated using Cohen’s *d* statistic, calculated as the difference in means divided by the pooled standard deviation. Cohen, 1988.

Table C1: Necessary Sample Sizes, Based on Effect Size Calculations from All Days ALPHA ERROR PROBABILITY=0.10, POWER=0.80

Measure	Effect Size	Necessary Total Sample Size
Total wait time	1.24	18
Response time	1.15	22
Request time	0.37	178
Cost-per-ride	3.02	6

Table C2: Necessary Sample Sizes for Total Wait Time Data Based on Effect Size Calculations, Days Separately ALPHA ERROR PROBABILITY=0.10, POWER=0.80

Day	Observation Area	Effect Size	Necessary Total Sample Size
1	Van Nuys/Valley Glen	0.74	48
2	Larchmont/Koreatown, Cypress Park/Elysian Valley/Lincoln Heights, Panorama City/Valley Glen/N. Hollywood	1.37	16
3	Larchmont/Koreatown, Cypress Park/Elysian Valley/Lincoln Heights	1.26	18
4	Cypress Park/Elysian Valley/Lincoln Heights	0.98	28

Table C3: Necessary Sample Sizes for Cost-per-Ride Data Based on Effect Size Calculations, Days Separately ALPHA ERROR PROBABILITY=0.10, POWER=0.80

Day	Observation Area	Effect Size	Necessary Total Sample Size
1	Van Nuys/Valley Glen	3.96	6
2	Larchmont/Koreatown, Cypress Park/Elysian Valley/Lincoln Heights, Panorama City/Valley Glen/N. Hollywood	3.00	6
3	Larchmont/Koreatown, Cypress Park/Elysian Valley/Lincoln Heights	2.78	6

APPENDIX D: NEIGHBORHOODS

Table D1: Neighborhoods (29) that met income and violence criteria in Los Angeles

Neighborhood	Population per Square Mile	Rate of Violent Crimes per 10,000 People	Median Household Income (\$)
Cypress Park	13478	35	42615
East Hollywood	31095	33.6	29927
Arlington Heights	21423	30.9	31421
Lincoln Heights	10602	28.7	30579
Adams-Normandie	21848	28.6	29606
Harbor Gateway	7720	28.1	47849
Koreatown	42611	27.8	30558
Boyle Heights	14229	27.6	33235
Lennox	21557	27.5	37937
Wilmington	5636	27.3	40627
Van Nuys	11542	26.4	41134
Mid-City / Arlington Heights	15051	24.5	43711
South El Monte	7150	24.4	46912
Lynwood	14264	22.9	48518
Highland Park	16835	21.2	45478
North Hollywood	13264	21.2	42791
Paramount	11395	20.6	49815
Echo Park	16868	20.5	37708
Valley Glen	12325	19.7	46175
Hawaiian Gardens	15141	18.8	46853
Larchmont	17747	18.5	47780
Pacoima	10510	18.3	49066
University Park	20217	17.9	18533
Panorama City	18028	17.7	44468
Chinatown	10568	14.2	22754
El Sereno	9826	12.1	45866
Walnut Park	22028	11.7	48750
Elysian Valley	9354	11.6	49013
Rosemead	10332	11.6	49387

Table D2: Neighborhoods Excluded (35) due to Violent Crime Rate > 35 per 10,000 People

Neighborhood	Rate of Violent Crimes per 10,000 People	Neighborhood	Rate of Violent Crimes per 10,000 People
Chesterfield Square	134.7	South Park	57.2
Harvard Park	122.2	Exposition Park	52.0
Vermont Vista	115.7	West Adams	50.8
Athens	109.9	Compton	49.8
Manchester Square	101.5	Historic South-Central	48.8
Vermont-Slauson	98.3	Jefferson Park	45.3
Vermont Knolls	96.4	Harvard Heights	45.1
Gramercy Park	94.0	Hollywood	44.3
Westmont	85.5	Willowbrook	44.3
Broadway-Manchester	84.1	Central-Alameda	42.4
Green Meadows	83.8	Elysian Park	41.4
Florence	79.2	Pico-Union	40.7
Leimert Park	76.4	Westlake	39.7
Vermont Square	66.9	Florence-Firestone	38.1
Baldwin Hills/Crenshaw	64.7	East Compton	37.0
Watts	62.9	Downtown	36.1
West Compton	62.5	Fairfax	35.2
Hyde Park	58.4		

NEIGHBORHOODS

SOURCE FOR NEIGHBORHOOD AREA SHAPE FILES: [HTTP://MAPS.LATIMES.COM/NEIGHBORHOODS](http://maps.latimes.com/neighborhoods)

DAY ONE

(TWO NEIGHBORHOODS)

Figure D1.1. Van Nuys

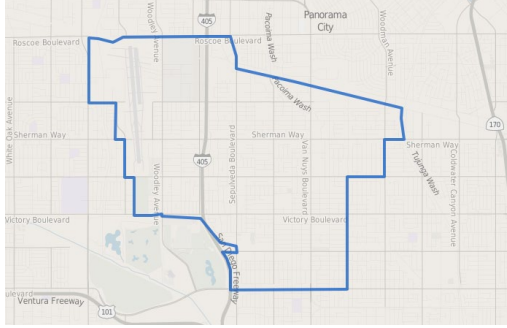
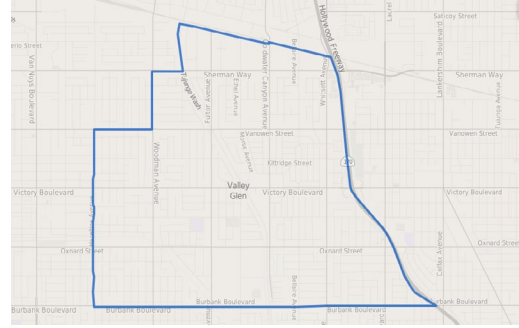


Figure D1.2. Valley Glen



DAYS TWO, THREE and FOUR

(NINE NEIGHBORHOODS)

Figure D2.1. Lincoln Heights

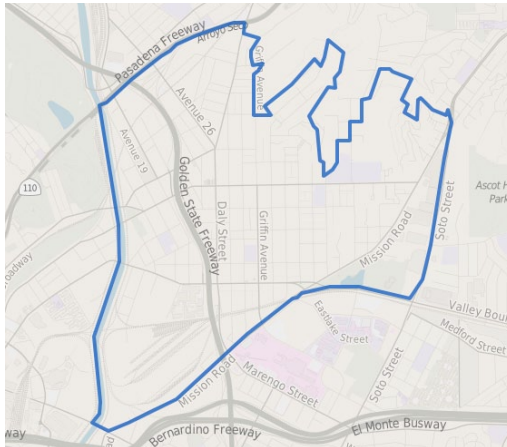


Figure D2.3. Cypress Park

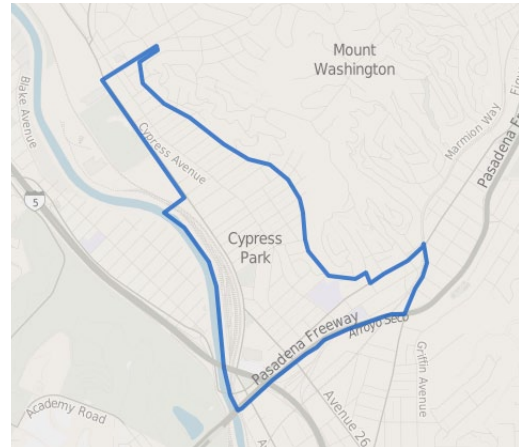


Figure D2.2. Elysian Valley

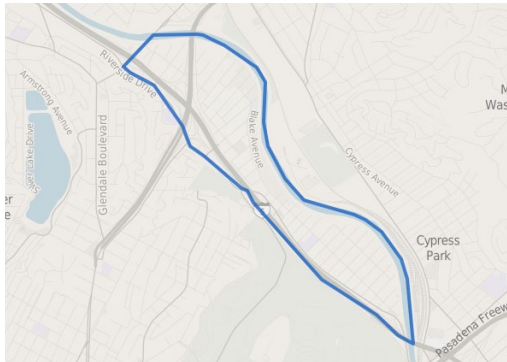


Figure D2.4. Koreatown



Figure D2.5. Larchmont

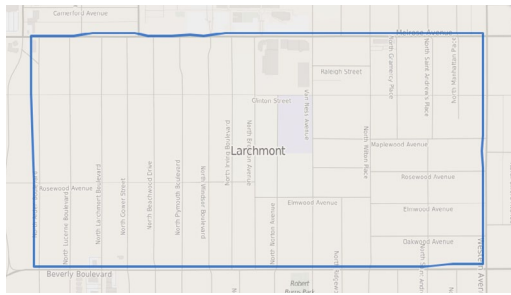


Figure D2.8. North Hollywood



Figure D2.6. Echo Park

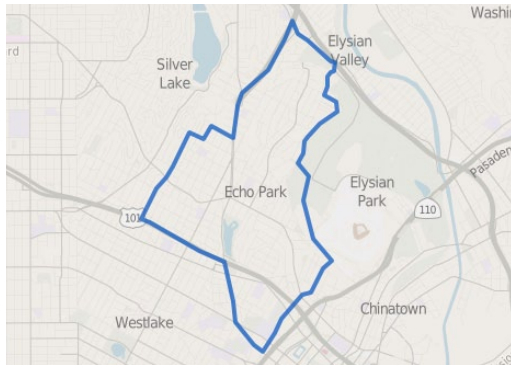


Figure D2.9. Valley Glen

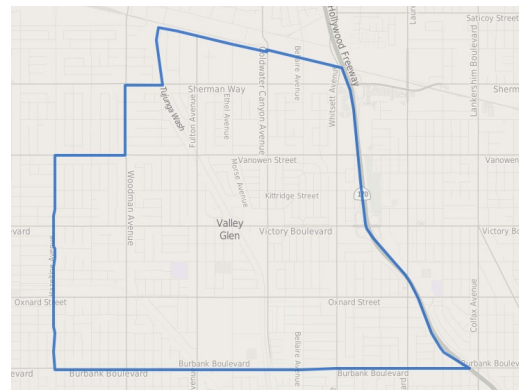


Figure D2.7. Panorama City

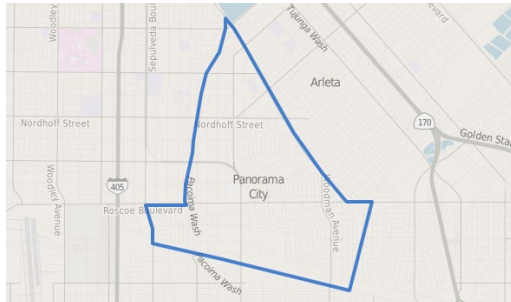
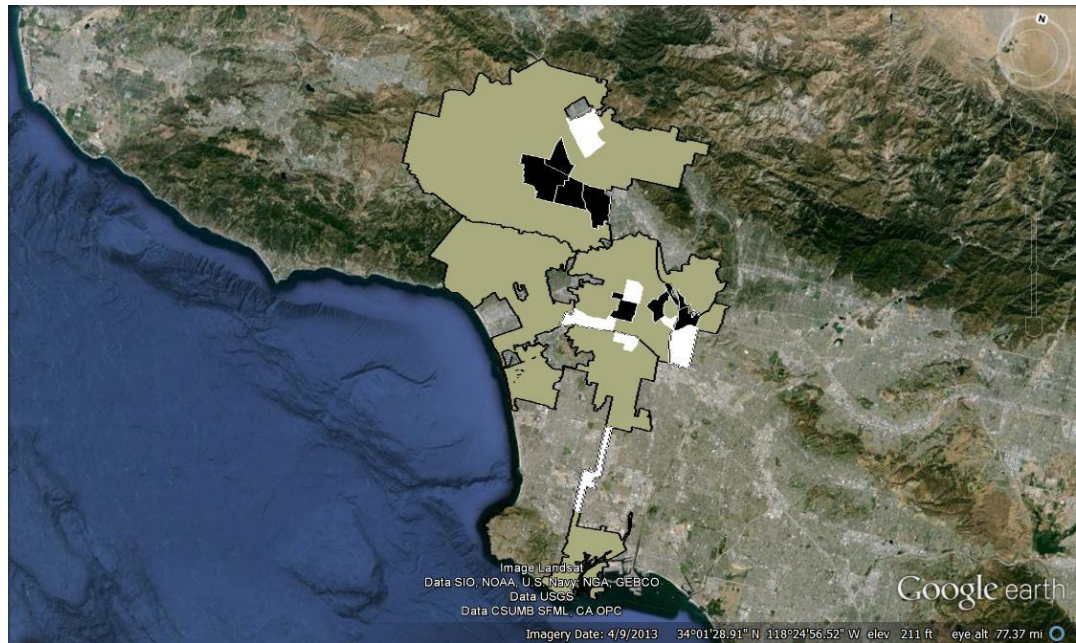


Figure D3.1: All, Qualifying Collected, and Qualifying Uncollected Neighborhoods



- ALL NEIGHBORHOODS WITHIN LOS ANGELES CITY LIMITS
- QUALIFYING NEIGHBORHOODS WHERE DATA WERE COLLECTED
- QUALIFYING UNCOLLECTED NEIGHBORHOODS

RESEARCH TEAM BIOS

Rosanna Smart

Rosanna Smart is a Research Associate at BOTEC and a Ph.D. candidate in the Economics at the University of California, Los Angeles (UCLA). Her research fields are applied microeconomics and public finance, and her current work examines the effects of regulated marijuana market growth on adolescent and adult substance use, as well as the mechanisms driving these behavioral changes. Prior to attending UCLA, she spent two years as a research assistant in the economic studies division at Brookings Institution. She also has an M.A. in Economics from UCLA and a B.A. in Mathematical Economics from Pomona College.

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Brad Rowe is the President and Managing Director of BOTEC. He is also Deputy Director for the Crime Reduction and Justice Program at NYU Marron. He provides project guidance and quality control for all BOTEC output. His areas of interest include crime and violence reduction, cannabis policy, and transportation policy. He has an M.P.P. from UCLA and a B.A. in Economics from the University of Wisconsin.

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Angela Hawken is a Senior Researcher at BOTEC and an Associate Professor at the School of Public Policy at Pepperdine University. She is also Director of the Swift Certain Fair (SCF) Resource Center at Pepperdine University for the Bureau of Justice Assistance. Currently, she is the Principal Investigator of several studies that test SCF strategies to reduce recidivism and incarceration. She has a Ph.D. in Policy Analysis from the RAND Graduate School and an M.A. in Economics from the University of Witwatersrand in Johannesburg, South Africa.

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Mark Kleiman is the Chairman of BOTEC and a Professor of Public Policy at the Marron Institute of Urban Management at New York University. He is also Director of the newly formed Crime Reduction and Justice Program at NYU Marron. His research areas include swift, certain, and fair sanctions programs and legal frameworks for regulating drugs such as cannabis, tobacco, and alcohol. He previously taught Public Policy at the Luskin School of Public Affairs at UCLA and at the Kennedy School of Government at Harvard University. He has both a Ph.D. in Public Policy and an M.P.P. from Harvard University.

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