Multi-Stage Stratified Cluster Analysis of Public Transit Fare Compliance

Brian Hanninen[1], Lori Rothenberg[2]
[1]Evaluation Cafe, 2213 Milwaukee Ave, Minneapolis, MN 55404
[2]North Carolina State University, 1000 Main Campus Dr., Raleigh, NC 27606

Abstract
There is no standard method for estimating fare evasion and fare compliance in North American transit agencies. Most transit agencies report on fare evasion as discovered by fare enforcement officials. Fewer transit agencies report on randomized sampling of transit users to estimate fare evasion and fare compliance. Reporting of the methodologies and results of the various sampling techniques are not shared widely. This paper examines the attempt of a North American transit agency to estimate fare evasion and fare compliance rates using a multi-stage stratified cluster random sampling methodology of its light rail transit lines. A baseline estimate was performed in 2014. Sampling was conducted again in 2016. This paper reports on the results of the sampling methodology and provides recommendations for implementing statistically sound fare evasion sampling in transit agencies. The substantive results of the study varied depending on the type of ticket/pass, time of day, rail line, zone, location, and direction of travel.

Key Words: Estimation, Compliance, Sampling, Cluster sampling, Stratified cluster sampling, Transit

1. Introduction

1.1 Statement of Purpose

Transit agencies rely on fare collection from transit users for major portions of their revenue. Frequently barriers are used to increase the likelihood that the transit users have paid a valid fare. Examples of barrier systems include paying fares to a bus operator and using gated entrances on rail and light rail train platforms. In some instances, a transit agency will decide to use a barrier-free system for its light rail train platforms. Reasons for relying on barrier-free systems include the avoidance of the upfront capital expenditures for barriers, as well as avoiding the continuing costs of staffing entrances. Barrier-free systems, though, come at a risk of higher fare non-compliance and evasion.

The purpose of this research is to describe the attempt of one transit agency to measure fare evasion on its light rail transit system. The following research questions will drive the study. What are the fare evasion rates over time? What explains variations in fare evasion? What lessons can be applied to measuring fare evasion for other barrier-free transit systems?

1.2 Significance of Study

Publicly reported studies of methodologies applied to estimate fare evasion are few. Reports of surveys of measures of fare compliance have been performed by the Transit

Cooperative Research Program. Detailed reports of methodologies applied by transit agencies, though, are not widely available.

This study will contribute to the dissemination of fare compliance estimation methodologies used by a transit agency. The results of the study will help to inform transit agencies on the choice of fare evasion estimation methodologies.

2. Methodology

The purpose of this study is to estimate fare evasion on the Blue Line and Green Line of the Metropolitan Council of the Twin Cities' light rail transit system in 2014 and 2016.

2.1 Research Objectives.

The basic research questions are:

- What is the fare evasion rate of the LRT system?
- What is the fare evasion rate on each of the two lines?
- What changes were there over time to the fare evasion rates?

The two primary research objectives, based on the research questions, are:

1. Develop a statistically verifiable method for estimating fare evasion; and
2. Identify improvements to the application of the methodology.

2.2 Research Design.

One of the researchers, while a member of the Program Evaluation and Audit department of the Met Council, designed the probability sampling method that employed multi-stage stratified cluster random sampling for the 2014 study. This sampling method provides statistically sound estimates for the overall population, but allows for a more efficient use of staff time. Twenty-five round-trip departures (12 on the Green Line; 13 on the Blue Line) were randomly selected, two for each of the following strata on each line: Weekday AM Peak, Weekday Midday, Weekday PM Peak, Weekday Night, and Weekend. Additional sampling periods were selected for time strata that had larger variations of estimates in the 2014 report. In 2014 twenty round-trip departures were randomly selected, two for each time strata on each train line.

For each round-trip, a car was randomly selected and then a section of the car. Any passengers that stood or sat in the randomly selected section were surveyed. Overall, the researcher and Audit staff asked a total of 915 passengers to show their proof-of-payment. The researcher and Audit staff wore Metro Transit safety vests and used mobile phone validators (MPVs) to check the fare compliance of passengers displaying electronic fare media. After reviewing the data collected, the 395 observations from the Blue Line and 520 from the Green Line were analyzed. Replicating the protocol from 2014, passengers who refused to show their proof-of-payment were not included in the analysis. Twenty passengers refused to show proof-of-payment – 9 on the Blue Line and 11 on the Green Line. Similar levels of refusals were observed in 2014 with six on the Blue Line and eight on the Green Line out of a total of 886 passengers surveyed.

In both studies "evasion" was defined as the following: (1) riding without any fare media; (2) riding with fare media more than one hour outside of the transfer period; (3) riding with electronic fare media that had expired or had never been activated; (4) riding with electronic fare media that had been reported stolen; (5) riding with fare media that is not valid on light rail, such as Super Saver Stored Value passes; and (6) riding with a Campus Zone pass outside of the allowed zone or on the Blue Line.

Passengers were given an additional one-hour grace period beyond the authorized 2.5-hour transfer period. This was in case the passenger boarded the train car during their transfer window, but only moved into the section being surveyed after the transfer period ended. This was identical to the protocol of the previous study.

When surveying on the Blue Line, the researcher and Audit staff observed which passengers boarded at the airport – but only checked the fares of passengers that continued traveling on the line beyond the free-fare zone. Passengers that traveled exclusively between Terminal 1 / Lindbergh and Terminal 2 / Humphrey stations were not surveyed.

Ridership estimates by time strata and special events were provided by Metro Transit Ridership and Revenue. These estimates were used to calculate post-sampling weights to reflect actual ridership patterns.

2.3 Theoretical Framework

This study used a complex sample design, namely multi-stage stratified cluster random sampling to estimate ridership and fare compliance. One commonly used technique to improve sampling efficiency is stratification (Smith 1993) and one common technique to reduce administrative costs is cluster sampling (Furth et al. 1988).

In considering statistical accuracy, stratified sampling is the most convenient option in that "*stratification of the population into groups can significantly improve the efficiency of sampling, resulting in either a smaller sample size to produce an estimate of equal precision, or an estimate of higher precision for the same sample size. To increase the efficiency, the variation between elements within the groups must be less than the variation between the elements when they are considered as one big group (i.e. the population)*" (Bucciarelli 1991, p.44). Thus, the researchers selected independent samples from each time strata and then estimated the population mean by post-weighting the sample based on the total number of days sampled during the sampling period.

"*While stratification of population improves the efficiency of estimation, clustering the sample can reduce the cost of collecting data*" (ibid, p.47). Instead of collecting the sample of interest randomly, researchers selected one-way passenger car trips as unit of measurement sequentially in time. Each stratum has two clusters (primary sampling units), namely an originating trip and the return trip. "*It is reasonable to assume that the ridership varies little between weekdays. Thus, a sample which contains all trips departing on one weekday will produce an estimate that is no less efficient than an estimate computed from a sample of the same size randomly selected from all departures over a month. In fact, if ridership varies significantly over time-of-day periods, the sample of all trips departing on a weekday is likely to be more efficient. It is much simpler and less expensive to measure ridership on all trips on the same day instead of some scattering of trips across all departures in a month*" (ibid, p.48). Clustering trips to obtain a statistical sample of cars is effective in reducing the cost of data collection.

2.4 Data Analysis.

Survey responses were entered in a Microsoft Excel Spreadsheet and then imported into SAS/STAT software.

Fields requiring analysis, such as, type of fare media, status of compliance, and status of evasion, were coded as numeric values. The column headings were adjusted to match the commands used in SAS/STAT 9.4, for example, "Weekday/End" was changed to "Strata" in the spreadsheet used for SAS.

Each observation was weighted by that time strata's share of ridership during the period sampled. The ridership estimates were provided to the researchers by Metro Transit's Revenue and Ridership department.

A primary sampling unit table needed to be created separately from the data spreadsheets. The primary sampling unit was the number of days sampled out of all possible days for each of the LRT lines.

Four models were run in SAS: Blue Line; Green Line; fare media (also used for estimating the overall fare evasion rate); and special events. The confidence intervals rather than the estimated means, were reported.

3. Results

3.1 Introduction

Using the multi-stage stratified cluster random sampling procedure described in the methodology section above, the researchers estimated the fare evasion rates for the METRO Blue and Green Lines. The 95% confident intervals were calculated and reported.

3.2 Overall Fare Evasion Rates

The overall fare evasion rate for the light rail transit system is between 8.3% and 10.4%. The larger ridership on the Green Line means that the overall rates are more closely reflecting the rates on the Green Line more so than on the Blue Line.

3.2.1 Blue Line

The Blue Line fare evasion rate is between 7.6% and 11.8%. For the Blue Line, the estimated fare evasion rate has increased compared to 2014. In 2014, the estimated range of fare evasion on the Blue Line was 2.6% to 3.6%. The reason for the increase in fare evasion on the Blue Line since 2014 is unknown.

3.2.2 Green Line

The Green Line fare evasion rate is between 8.4% and 10.8%. Since the confidence intervals for the estimated fare evasion rates of the Blue Line and Green Line overlap, it indicates that there is no statistically significant difference between the evasion rates for the two lines.

The Green Line has a higher fare evasion rate than in 2014, but the overlap of 95% confidence intervals indicates that the true fare evasion rate may not have changed. The fare evasion rate in 2014 ranged from 4.6% to 9.0%.

3.3 Evasion by Time Strata

At all times of day, passengers should have valid proof-of-payment for their fare, or identification for being allowed to ride free (peace officer, disabled veteran, etc.). Audit in 2014 sampled a minimum of two round trips during each of the following time strata:

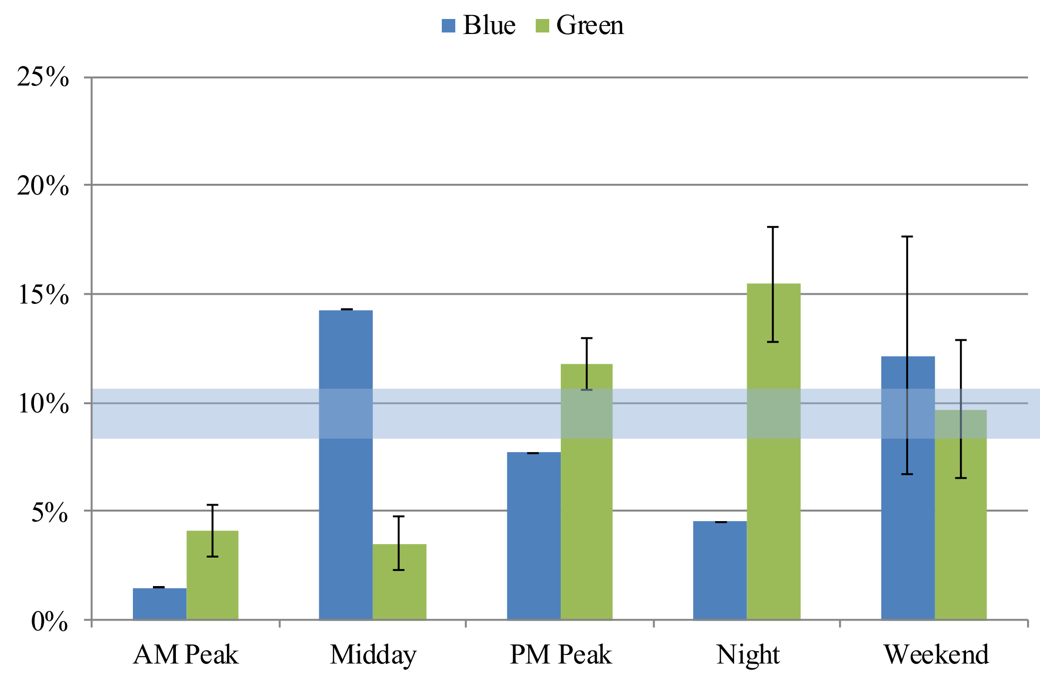
- AM Peak
- Midday
- PM Peak
- Night
- Weekend

The researcher in 2016 increased the number of sample round trips for time strata that had lower sample sizes in the 2014 study. On the Blue Line, three round trips were sampled during Midday, Night, and Weekend times. On the Green Line, three round trips were sampled during Night and Weekend times.

It should be noted that "Night" data was only collected from the end of PM Peak until 10:00 PM. Therefore, conclusions about evasion at night may not reflect the behavior of passengers that ride between 10:00 PM and 6:00 AM the next morning.

3.3.1 Comparison between Blue and Green Lines

Midday has higher evasion on the Blue Line than the Green Line, and evasion is higher on the Green Line at AM Peak, PM Peak, and Night. Figure 1 presents a comparison of fare evasion by time for the Blue and Green Lines. The bars show the mean estimates and the lines demonstrate the 95% confidence intervals. Fare evasion is higher Midday on the Blue Line compared to the Green Line. Fare evasion on the Green Line is higher than the Blue Line during AM Peak, PM Peak, and Night. The overlap of confidence intervals during the Weekend service time indicates that there is not a statistically significant difference in mean evasion.

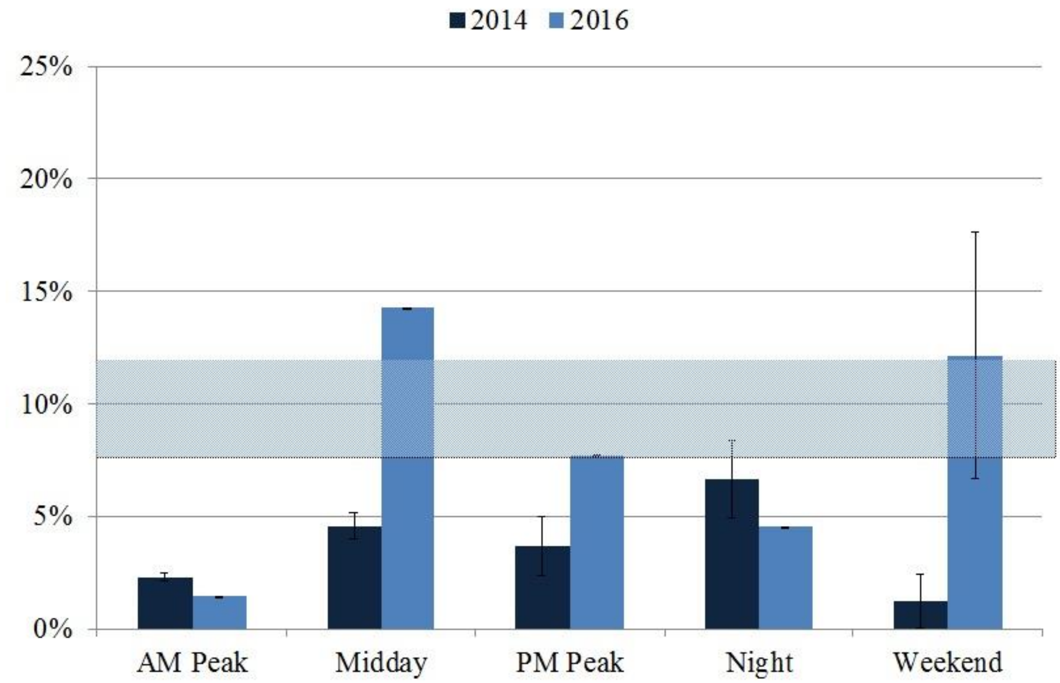


Note: Shaded area is the range of estimated evasion for both Blue and Green lines.
Figure 1 | *Fare evasion by time*

The relatively low fare evasion during Night on the Blue Line is surprising – generally, nights and weekends would be expected to have relatively high fare evasion based upon the review of previous studies of fare evasion. (TCRP synthesis 96, 2002, p.43) On the Green Line, the low evasion during Midday compared to PM Peak is also unexpected.

3.3.2 Blue Line time strata comparisons

Fare evasion in 2016 has increased on the Blue Line during Midday, PM Peak, and Weekend times and it has decreased during AM Peak and Night compared to 2014 estimates. Figure 2 presents a comparison of fare evasion by time for the Blue Line in 2014 and 2016. The fare evasion rate has increased substantially during the Midday, PM Peak, and Weekend service times. AM Peak and Night service times experienced smaller, but statistically significant decreases in fare evasion.

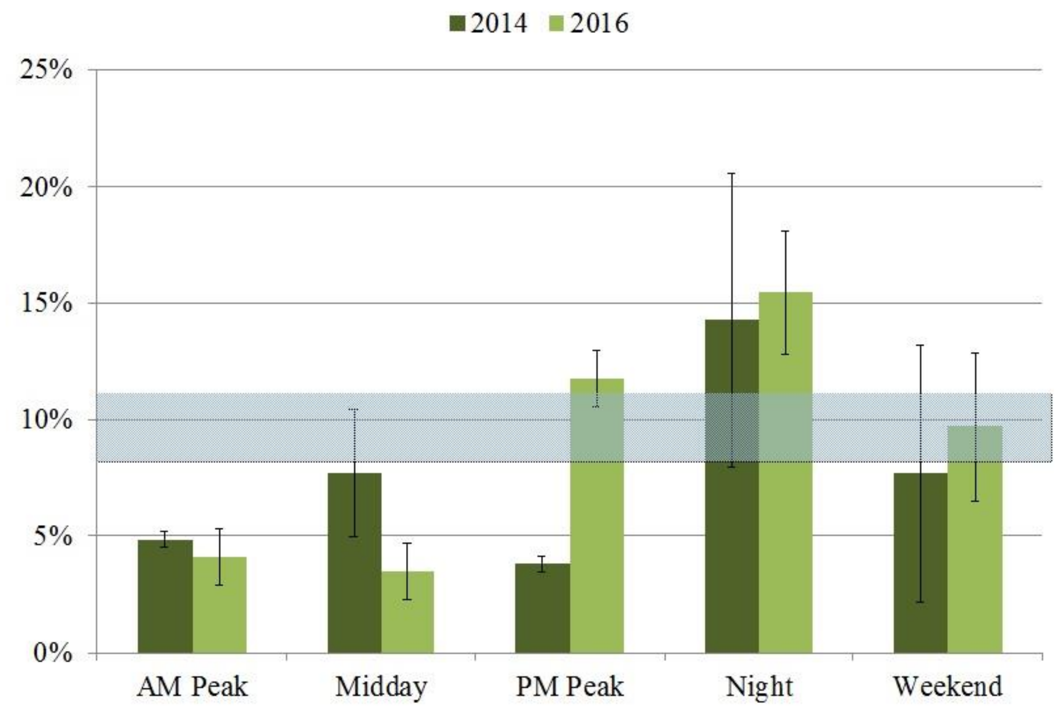


Note: Shaded area is the range of estimated evasion for Blue Line in 2016.
Figure 2 | *Blue Line fare evasion by time comparison 2014 & 2016*

The substantial increases in fare evasion may be the result of the publicity surrounding the change of fare enforcement policy by Metro Transit police during the spring of 2016. The policy announced was that all first-time fare evaders would be issued warnings. The second incident of fare evasion would be a citation with a fine of $180. That may have made some riders more willing to risk riding without proof of payment knowing that a warning would be issued, rather than a citation.

Also, fare evasion in 2014 may have been suppressed by fare enforcement actions that year. As police staffing was increased in preparation for the opening of the Green Line in June 2014, fare enforcement patrols increased on the Blue Line. The greater frequency of fare enforcement activity earlier in 2014 may have reduced riders' willingness to ride without proof of payment into the summer and fall of 2014.

3.3.3 Green Line time strata comparisons
Fare evasion in 2016 has increased on the Green Line during PM Peak, and it has decreased during Midday compared to 2014 estimates. Figure 3 presents a comparison of fare evasion by time for the Green Line in 2014 and 2016. The fare evasion rate has increased substantially during the PM Peak service time. Midday service time experienced a statistically significant decrease in fare evasion. The other time strata did not have statistically significant changes in fare evasion.



Note: Shaded area is the range of estimated evasion for Green Line in 2016.
Figure 3 | *Green Line fare evasion by time comparison 2014 & 2016*

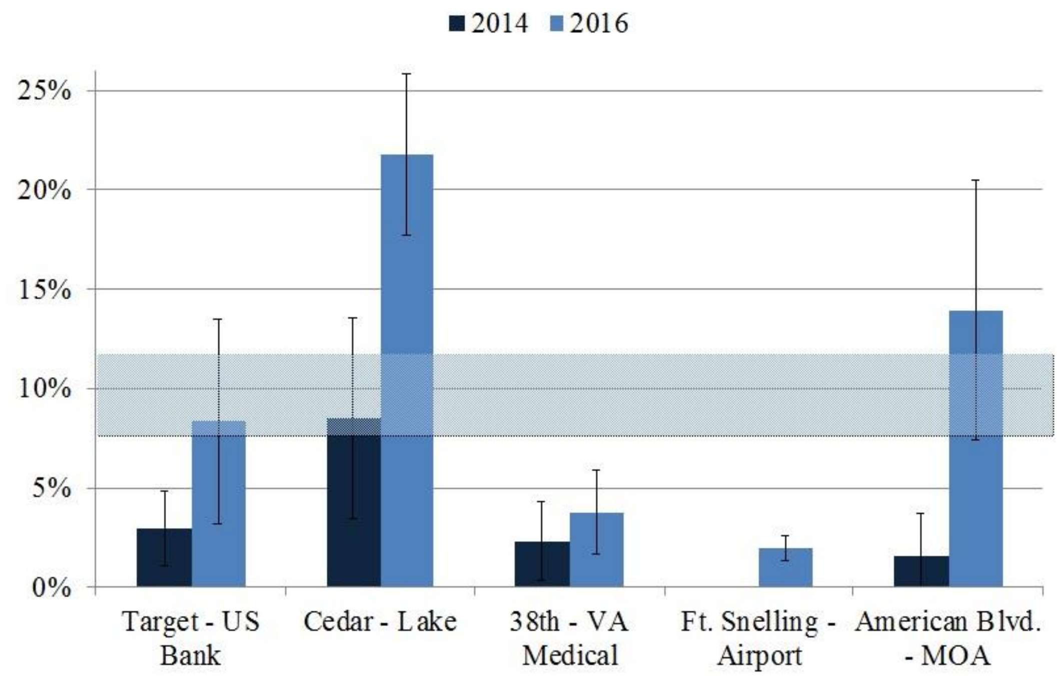
3.4 Evasion by Location.

This study separated each line into five zones, each zone covering about four or five stations. For the most part, passengers were surveyed upon immediate entrance onto the train.

The variance of fare evasion by zone can be quite large, so making conclusive statements using this data can be difficult. However, some general trends are apparent in the estimates.

3.4.1 Blue Line

On the Blue Line, evasion may be highest between Cedar-Riverside and Lake Streets. Figure 4 shows the evasion rates among the five zones along the Blue Line compared to 2014. In terms of evasion on the Blue Line, evasion between Cedar Avenue and Lake Street – the midtown area of Minneapolis and adjacent to the downtown – stations is between 18 percent and 26 percent. The lower estimate for this zone could even be lower than the higher estimates for American Boulevard to Mall of America stations. The remaining three zones have the lowest evasion rates.

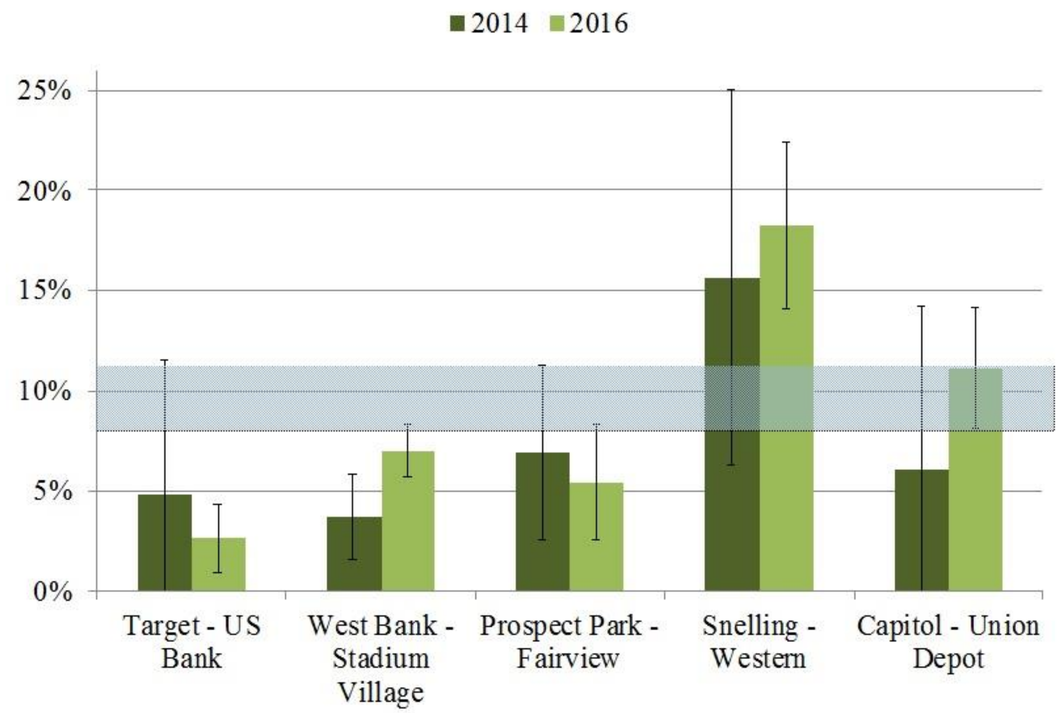


Note: Shaded area is the range of estimated evasion for Blue Line in 2016.
Figure 4 | *Blue Line fare evasion by zone comparison 2014 & 2016*

The higher evasion rates in the Cedar-Riverside to Lake Street zone, Fort Snelling to Terminal 2 stations, and American Boulevard to Mall of America stations zones are statistically significantly higher compared to the results from 2014. No evasion was found in the Fort Snelling to Terminal 2 / Humphrey zone in 2014.

The researcher looked at both the frequency of fare evasion in each zone by time period. The occurrences of passengers without proof of payment were adjusted by the estimated ridership for that time period. This adjustment allows a comparison of the likelihood of detecting fare evasion within a zone, however, the number of riders boarding within a zone is not accounted for. Zones with high ridership would tend to have greater frequency of fare evaders all things being equal.

3.4.2 Green Line
On the Green Line, evasion may be highest between Snelling Avenue and Western Avenue. Figure 5 shows the evasion rates among the five zones along the Green Line in 2014 and 2016. In terms of evasion on the Green Line, evasion is between 14 percent and 22 percent between Snelling and Western stations, the zone adjacent to downtown St. Paul. The lower estimate for this zone could even be lower than the higher estimate for Capitol / Rice to Union Depot stations. The remaining three zones have lower fare evasion compared to the zones on the eastern end of the line.



Note: Shaded area is the range of estimated evasion for Green Line in 2016.
Figure 5 | *Green Line fare evasion by zone comparison 2014 & 2016*

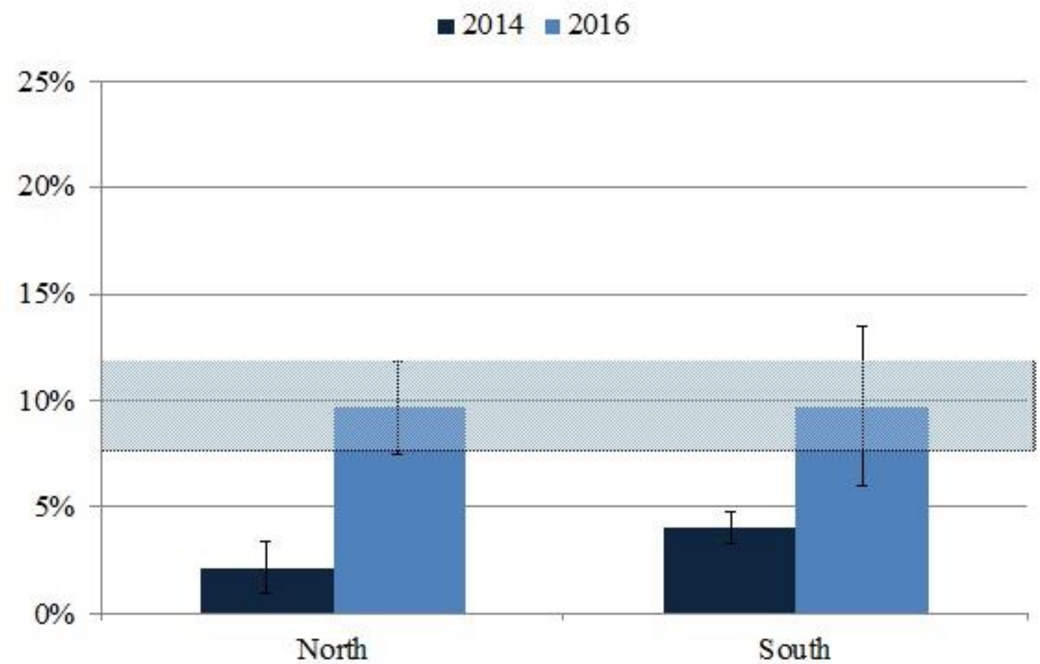
The changes in fare evasion in all the zones are not statistically significant compared to the survey results in 2014 with the possible exception of the West Bank to Stadium Village zone, the area within the campus of the University of Minnesota, Twin Cities. The overlap of confidence intervals in that zone prevent declaring a definitive conclusion that fare evasion has increased. Unlike the 2014 survey results, it appeared that University of Minnesota students that did not have proof of payment were seemingly native English speakers.

3.5 Evasion by Direction

Fare compliance and evasion by direction on each line were analyzed.

3.5.1 Blue Line

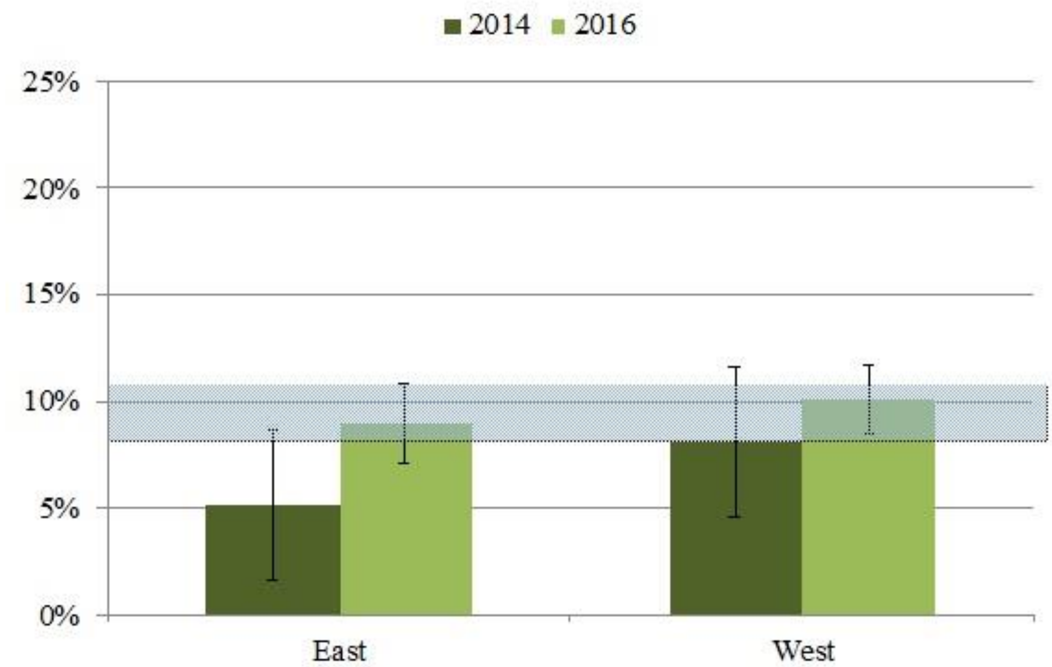
On the Blue Line, evasion is likely the same in both directions and is higher than in 2014. Figure 6 shows the evasion rates for each direction on the Blue Line in 2014 and 2016. Fare evasion rates are not significantly different for northbound and southbound trips.



Note: Shaded area is the range of estimated evasion for Blue Line in 2016.
Figure 6 | *Blue Line fare evasion by direction 2014 & 2016*

The increases in fare evasion since 2014 are statistically significant.

3.5.2 Green Line
On the Green Line, evasion is likely the same in both directions and may be the same as evasion rates in 2014. Figure 7 presents the evasion rates for each direction on the Green Line. The confidence intervals for evasion estimates on the Green Line overlap, indicating evasion is likely not different in the two directions.



Note: Shaded area is the range of estimated evasion for Green Line in 2016.
Figure 7 | *Green Line fare evasion by direction 2014 & 2016*

Fare evasion increases compared to the 2014 survey results are not statistically significant. Fare evasion rates may be the same on the Green Line in 2016 as in 2014.

4. Limitations

4.1 Population

The fare evasion estimates presented in this report are valid only for the population of passengers that are required to show proof-of-payment on light rail. That population does not include children five years-old or younger, personal care attendants traveling with disabled passengers, nor passengers traveling for free on the "airport shuttle" between Terminal 1 / Lindbergh and Terminal 2 / Humphrey stations. Therefore, it would be an overestimate to take the total number of riders on either line and multiply it by the evasion rate to come up with the total number of riders that evade. When this report states that the evasion rate on the Blue Line, for example, is X%, that isn't the evasion rate for all passengers. Instead, it is the evasion rate for passengers that are required to show proof-of-payment. Therefore, the evasion rate calculated for this study accurately represents the evasion rate for the population about which Metro Transit is interested.

4.2 Time Frame

For the probability sampling method, departure times were chosen so that the earliest trips began at the start of AM Peak and the latest trips ended by 10:00 PM. Therefore, any inferences based on the 95% confidence intervals in this study should be only for the population that rides between about 6:00 AM and 10:00 PM. The rates estimated in this study cannot be said to explain the fare evasion of passengers that ride very late at night or early in the morning.

4.3 Identification

The researcher and Audit staff did not request to see the identification of passengers traveling with discounted fares, nor the identification of those riding with electronic passes that do not have identifying information already on them (such as U-Passes). Generally, the researcher and Audit staff only inquired about the proof-of-payment for children that appeared to be at least six years old. Therefore, this study assumed that someone with a discounted fare had paid the correct fare, and that people carrying pre-paid passes were the authorized users.

4.4 Refusals

Refusals of riders to show proof of payment are not included in the analysis of fare evasion or compliance. This issue can cause non-response bias, if the passengers that refuse are systematically different from the general population.

4.5 Seasonality

Also, it should be noted that sampling took place during four weeks in April and May. If the fare payment behavior of passengers is somehow very different at that time of the year compared to others, the fare compliance and evasion rates estimated may not accurately reflect those of different times. The 2014 study sampled passengers during the autumn months. Sampling along the Green Line in this report occurred while classes were in session at the University of Minnesota to ensure that students are represented in the sample, thus, attempting to replicate the sampling conditions of the first study.

5. Recommendations

Barrier-free light rail transit systems need enforcement of fare payment whether that is performed by uniformed peace officers or authorized transit staff. A replicable random sampling protocol should be used to measure how fare evasion is changing over time.

Multi-stage stratified cluster random sampling design allows for efficient allocation of staff resources while maintaining high levels of precisions for the estimates. (Bucciarelli 1991)

5.1 Ridership Estimates

Fare evasion studies should report on the estimation of ridership levels used by the transit agency. Care must be taken to obtain sufficiently large sample sizes. The precision of the estimates depends on the transit agencies' precision of estimating ridership levels during the sampling periods. This study benefits from Metro Transit's use of automated passenger counters (APCs) on more than half of the train cars in operation. The use of APCs has given the transit agency greater precision of its ridership estimates. Reporting fare evasion sampling results should also acknowledge the reliability of the ridership estimates.

5.2 Inference of Causal Factors.

Further study is required to determine the reasons for variations in fare evasion across time and location. Changes in fare evasion are due to several causes besides enforcement activities. These causal factors may include socioeconomic demographics of the transit population, risk adverseness of transit users, fare costs, and fare evasion penalties. Deducing why certain times of day or station areas experience greater and lesser fare evasion requires further study on the part of the transit agency. Further sampling of transit users to gather information that may influence fare evasion behavior, for example, socioeconomic factors, would help to confirm the factors that influence fare evasion rates.

5.3 Data Collection Errors

Interviewers should be trained to conduct sampling to allow for little to no variation between interviewers in determining whether a fare is compliant. Errors and variability of individual interviewers can cause errors in the data. Variation in determination of fare compliance was mitigated somewhat in the 2014 by having one of two interviewers present on all data collection events. In 2016 one interviewer was present for all data collection events.

Data should be double-checked for accuracy when possible. Data was collected manually with the interviewer noting on paper the fare type, compliance, and reason for non-compliance. Although each sample is recorded on an individual sampling record, errors had occurred through duplication of records. The errors were found by comparing the manually collected to the data collected by the mobile phone validators that each interviewer used to check the status of electronic fare media. That still leaves some paper media from being verified after data collection.

References

Bucciarelli, M. (1991). Cluster sampling methods for monitoring route-level transit ridership. Massachusetts Institute of Technology: Operations Research Center.

Chu, Xuehao. (2005). Ridership accuracy and transit formula grant. The 2005 Transportation Research Forum Annual Meeting.

Fuller, W.A. (1975). Regression analysis for sample survey. *Sankhya*, *37* (3), Series C, 117 – 132.

Furth, P.G., Killough, K.L., & Ruprecht, G.F. (1988). Cluster sampling techniques for estimating transit system patronage. *Transportation Research Record 1165*, 105 – 114.

Gupta, D., & Chen, Y. (2014). Statistical analysis of fare compliance: Task 4 draft final report. University of Minnesota: Center for Transportation Studies.

Metropolitan Council Program Evaluation and Audit. (2008). Hiawatha light rail fare compliance. Metropolitan Council of the Twin Cities: Audit Committee.

Metropolitan Council Program Evaluation and Audit. (2010). NorthStar commuter rail: Fare compliance and ridership estimates. Metropolitan Council of the Twin Cities: Audit Committee.

Rocha, A. (2015). Subsampling with a survey sampling design? DOMAIN idea is to get an appropriate variance estimate. University of Washington: Center for Studies in Demography and Ecology.

Smith, R.L. (1993). Development of cost-effective sampling plans for section 15 and operation planning ride checks: Case study for Madison, Wisconsin. *Transportation Research Record 1402*, 28 – 89.

Transit Cooperative Research Program. (1996). TCRP report 10: Fare structures, policies, and Technologies.

Transit Cooperative Research Program. (2002). TCRP report 80: A toolkit for self-service, barrier-free fare collection.

Transit Cooperative Research Program. (2002). TCRP synthesis 96: Off-board fare payment using proof-of-payment verification.

Woodruff, R.S. (1971). A simple method for approximating the variance of a complicated estimate. *Journal of the American Statistical Association*, *66*, 411–414.