What is the effect of an increase in fares on fare evasion?

FA23-ECON-381-01 Michelle Dong

Introduction

As "the world's largest single rapid transit service provider by number of stations (472 stations in total)", the New York transit system is pretty well known ("New York City Subway," 2023). Aside from the constant delays, ridiculous subway encounters, and lack of cleanliness, a big topic for most New Yorkers is the fares. Fares are without a doubt an integral part of the public transit system; they cover operating costs and maintenance expenses, implementation of new technologies, and overall safety and security. While fares are important, they are also barriers, especially for people with low income and people who actually have to depend on public transit. Despite the high cost of living, there is a high percentage of people in NYC who are in poverty, 17% as compared to the US average of 11.5% (US Census, 2022). When this is the case, you have to think about fares from a new perspective.

On August 20, 2023, the MTA raised fares to \$2.90 from the \$2.75 that has been in effect since 2015. For many, this change was very well justified by the idea of inflation and overall rising costs, but for many others, it was outrageous but there wasn't much they could do about it (Nicastro, 2023). Though a result of a variety of factors, it is only reasonable to assume that because of unaffordable fares, some people resort to fare evasion. This paper seeks to determine the relationship between fare and fare evasion; and despite fare evasion being a result of a variety of factors, the causal effect of an increase in fares on fare evasion. I will investigate the extensive margin: "Does increasing fares cause fare evasion?" and the intensive margin: "Conditional on there being fare evasion, does increasing fares increase the number of fare evasion?".

Literature review

Existing literature along the lines of public transit and fares looked at aggregate data before and after a fare increase to analyze the gross effect of a fare increase, effect of fare

increase by time of day, effect on journey to work, effect on different economic status, and effect on riders paying more than one fare (LASSOW, n.d.). The author compared the number of regular fare passengers before and after the fare increase in July 1966 on the NYC transit system, a fare increase from 15 cents to 20 cents. Without accounting for other factors that influence transit riding, Lassow found that on the aggregate, a 1 percent increase in fare is associated with a 0.3 percent decrease in ridership with effects varying by time of day, type of rider, and type of travel. With respect to my topic, the author found that there was a 8.6% decrease in ridership for low income riders compared to a 2.7% decrease for "commuters". In general, it has been pretty well established that as fares increase, ridership decreases; with differential effects that could be explained by riders' fare elasticity. Though many factors play a role, fare elasticity provides one perspective to understand the change in fare evasion as a result of a change in fare. For example, a highly inelastic consumer may not be able to pay the fare and have to resort to fare evasion as opposed to a rider with low willingness to pay but is super elastic and would just not ride. Within NYC transit systems, research has shown that unlimited ride options also plays a role in fare elasticity, specifically, people using unlimited ride metrocards were less sensitive to changes in fares (Hickey, 2005).

In a study looking at the psychology behind fare evasions, researchers tried to understand the motivation behind fare evasion and the characteristics that make someone more likely to fare evade. They categorize fare evaders into 4 categories by their intention and attitude: the accidental evader, the "it's not my fault" evader, the calculated risk-taker and the career evader. In general, people evade because of barriers ("it's not my fault" evader), evasion because of low risk (calculated risk-taker), and also just because they want to (career evader) (Public Transport

_

¹ Riders in this case are categorized by the area of the station and the economic status of that area; "commuters" are defined as riders in the midtown area, presumed to be of higher economic status

Research Group, 2015). In a similar vein, people evade because they have a certain perception of the subway system; for example, feeling that their fare isn't getting put to good use or if it was socially acceptable to fare evade (Gloria, 2018).

Additionally, within the NYC subway system, fare evasion is also affected by payment methods. People have found cracks within the technology of metrocards, allowing them to get "swipes" without paying for anything (McClain, 2019). To add, NYC has recently introduced new methods of paying for fares, where you can tap to ride. This is associated with people sharing stories about how they have used empty gift cards to "pay" for rides. Though interesting and potentially important, controlling for the change in payment method on fare and fare evasion will complicate my model too much and as such, I will focus on the time before the new payment method was really prominent: before 2022.

Reading less formal literature related to fare evasion in NYC there are increasing concerns over equity: where people are noticing more criminalization in low income areas and for people of color (Report of the Blue-Ribbon Panel, 2023) (Wagner, 2020). Consequently, new policies have focused on shifting towards issuing summons and verbal warning as opposed to arrests². Even with the shift to summons, there are still concerns with summons being disproportionately issued to people of color and in low income areas.

Building off the literature, I want to determine the causal relationship between fare and fare evasion by taking into account the fact that the effect of fare on fare evasion might vary depending on income level, considering the psychology behind evasions, noting the influence of payment methods, and taking into account potential effects of discrimination within the system.

Theory

² Summons are tickets, indicating a fine amount from \$50 to \$100 that you can pay or dispute at a hearing

Looking at the relationship between fare prices and fare evasion, a simple theoretical model is guided by the supply and demand framework. We have prices set by the MTA, Metropolitan Transportation Authority, and people's willingness to pay. In the case of fare evasion, we might understand it as: people riding the subway even though they have willingness to pay below the price line. Taking into account our literature, we want to also include people's perception of the subway system which is subject to police involvement, people feeling higher risk, and perceived quality of service. Additionally, we might also include payment methods to account for different elasticities with different metrocards and tap to pay. Our ideal model would be: $Number\ of\ fare\ evasion = F(Subway\ demand, Fare\ Price, Perception, Payment)$. The problem we have is not knowing subway demand or people's willingness to pay. As such, we should include in our model, factors that influence or correlate with subway demand: income and ridership. Our model being

Number of fare evasion = F(Income, Ridership, Fare Price, Perception, Payment), with the corresponding causal diagram, Figure 1. We expect that as fares increase, the number of fare evasions will increase; as income increases, willingness to pay increases, and fare evasions decrease. I expect that there is a nonlinear relationship between fare evasion and ridership: where fare evasion is more likely to occur if there are very few riders or a lot of riders, and less if there is an average number of riders. I expect that if people's perception of the subway system is good and they feel a high risk of getting caught for fare evasion, the number of evasions would decrease. If payment is more flexible and people can get away with not paying, fare evasion would increase.

Data Description

The datasets I used to capture fare evasion comes from fare evasion summons reports shared by the NYPD. These datasets are reported quarterly since 2017q4 and are organized by stations, recording the number of arrests at each station, tallying the gender, race, and age of the offender. For my project, I used data from 2017q4 to 2021q4³ which includes 4,072 observations across 292 stations. These observations represent only stations with summon counts during the quarter and don't include stations without any summons. To reconcile this, I created a dataset with all the stations such that zeros are observed for stations without any summons during the quarter.

Since fares during this time period have remained constant nominally, variation arises from considering inflation and real fares by using the CPI. Using CPI for all items in NY-NJ-PA, all urban consumers, not seasonally adjusted published by the U.S. BUREAU OF LABOR STATISTICS, we calculated the real fare for each quarter in 2021q4 dollars. To include ridership, the NYC MTA shares subway ridership data detailing the annual total ridership at each station for years 2017 to 2022.

In terms of income, while we might not have individual level information, we want to get a sense of the income in the area around the subway station as it gives more context to the riders and offenders. We began by locating the neighborhoods of the stations and using data from the United States Census Bureau, ACS PUMS, which details the average family income during the past year of NYC districts, we ultimately matched stations to neighborhoods, neighborhoods to districts, and districts to income. With this data, we don't have variation in income at the neighborhood level but rather at the district level, which is a limitation. When merged with the station dataset, observations of stations in the same district and in the same year will have the

_

³ Excluding 2020q4 because the dataset is incorrect

same average income. As before with fares, we also want to consider real income in 2021q4 dollars.

Ultimately, after all merges and accounting for outliers, our master dataset contains 4,798 observations across 300 stations showing the number of fare evasion summons, ridership, and average income of each station during each quarter from 2017Q4 to 2021Q4⁴.

My dependent variable is the number of fare evasion summons with variation across stations and quarters and main independent variables are real fares with variation across quarters, ridership with variation across stations and years, and average family income with variation across districts and years.

We want to note that due to our measure of fare evasion being proxied by summons, we are technically not measuring the number of fare evasions but rather the fare evasions that are caught and have been offered a summon. From our literature, we have to consider potential discriminatory effects that may lead particular areas or groups of people to be caught at a higher probability.

Looking at the summary statistics, Table 1, we can see that we should consider logging our variables based on their range, skew, and kurtosis: specifically summons for ALL PERSONS, Real AVG Family Income in 2021 Q4 Dollars, and Ridership. Looking at the k-density plots for these variables and making sure that their interpretation makes sense in ratio rather than levels, these variables should be logged. To get a general idea of the relationship between real fares and number of summons, Figure 2, we looked at the overall trends over time and in relation to each other. In consideration of our empirical model, we want to look at the relationship between our main regressors and our outcome: real fares and logged summons,

⁴ Due to merging multiple datasets, the master dataset only includes observation across 300 station out of the 472 total stations

Figure 3; logged ridership and logged summons, Figure 4; and logged real income and logged summons, Figure 5.

Empirical theory

My empirical model follows from my theoretical model, introductory data visualizations, and literature review. From the literature, Lasso found differential effects on ridership between people of different income levels, suggesting for my model interaction between real fares and logged income. Testing possible interaction effects, Figure 6, our data reflects the literature. Though there doesn't appear to be a nonlinear relationship within our visualization between ridership and summons, we justify the inclusion of a quadratic log ridership term based on our intuition and a rough prior on consumer crime behavior. Using panel data and having concerns about other variables that I might not have considered, I included fix effects for years and neighborhoods to absorb variation from potential omitted variables that could lead to bias. We note that fixed effects only adjust for bias from variables that vary only across years or only across neighborhoods, an example being location of the station.

My empirical model specifications:

Extensive margins:

```
Pr(hasSummons_{s,q} == 1) = \beta_0 + \beta_1 realFares_q + \beta_2 log(RealIncome_{d,y}) + \beta_3 realFares_q : log(RealIncome_{d,y}) + \beta_4 log(ridership_{s,y}) + \beta_5 log(ridership_{s,y})^2 + \alpha_y + \alpha_n + \epsilon_{s,q}
```

Intensive margins:

```
log(Number of Fare Evasion Summons_{s,q}) = \beta_0 + \beta_1 real Fare s_q + \beta_2 log(Real Income_{d,y}) + \beta_3 real Fare s_q : log(Real Income_{d,y}) + \beta_4 log(rider ship_{s,y}) + \beta_5 log(rider ship_{s,y})^2 + \alpha_y + \alpha_n + \epsilon_{s,q}
```

and associated causal diagram, Figure 7.

Evident from the data description and empirical model specification, we are unfortunately unable to include perception and payment from our theoretical model in our empirical method. Since perception of the subway system and the type of payment methods people use varies by both neighborhood and over years, our fixed effects cannot control for the variation from these two variables. As such, we are concerned about omitted variables, especially since there is a correlation between perception and fares and correlation between perception and fare evasion, and the same with payment methods as well.

Results

Looking at the results for the extensive margin under the preferred specification, Table 2, we see that a one unit increase in real fares is associated with a 3.2% - 2.9% * logIncome increase in the probability that a person fare evades, holding all else constant. We understand this as the effect of fare on the probability of fare summons varies depending on the income of the area: the increase in real fares is associated with increased probability of fare evasion summons for low income areas and decreased probability of fare evasion summons for high income areas. Though this result is economically significant and matches our intuition, suggesting a predictive effect of fare on fare evasion summons, it is not statistically significant at the 1%, 5%, and 10% level and we do not have enough evidence to suggest that the relationship between fare and he probability of fare evasion is distinguishable from zero. With this being the case, we want to look at the estimates for our regressors, specifically income and ridership and compare it to our intuition. We observe that the coefficients are also mostly statistically insignificant and the direction doesn't correspond to our intuition. Our model suggests that an increase in income is associated with higher probability of fare evasion summons, and there is higher probability of fare evasion summons for average levels of ridership compared to the extreme ends. To test for

the robustness of our model, we ran the same regression using probit and logit models, Table 3. In general, the results are relatively similar across models in that the direction of our estimates for the variables are similar, it is interesting to note that the estimates for probit and logit both match our intuition for the nonlinear relationship between ridership and fare evasion better.

Since we are cautious about the differential effects across race groups, we want to ask "Does increasing fares cause fare evasion differently across different race groups?" In considering this question, rather than focusing on whether there are summons for anyone, our outcome variables will be whether there are summons for the particular race group. The results are shown in Table 4. We observe that the results are particularly different for Black and Hispanic as compared to American Indian and Alaskan Native, Asian Pacific Islander, and White. Observing these results and differences, there could be further investigation looking at the specific effects of race on fare evasion summons.

Looking at the results for the intensive margin under the preferred specification, Table 5, we interpret the coefficients on fare to be a one dollar increase in real fare is associated with a -300.5 + 1.9 * Income change in number of fare evasion summons given that there is fare evasion, holding all else constant. We interpret this as given that there are fare evasion summons, the effect of fare increase on the number of fare summons varies depending on the income of the area: an increase in real fares is associated with a decrease in fare evasion summons in low income areas and an increase in fare evasion summons in high income areas. This result does not match my intuition as I would expect an increase in fare to be associated with an increase in fare evasion and the interaction between fare and income to go in the other direction: the effect of fare on fare evasion should decrease as income increases. Ultimately, our coefficient estimate is not statistically significant at the 1%, 5%, and 10% level and we do not have enough evidence to

suggest that the relationship between fare and fare evasion is distinguishable from zero. Briefly looking at the coefficient estimates for our control variables, they do not match my intuition and they are also statistically indistinguishable from zero. Running a simple robustness test on a randomly selected half of the observation we get the same results, .

As before, we want to ask "Conditional on there being fare evasion, does increasing fares increase the number of fare evasion differently for different race groups?" Now, rather than having the outcome variable be $Log(Number\ of\ fare\ evasion\ summons)$ our outcome variables will be $Log(Number\ of\ fare\ evasion\ summons\ for\ a\ particular\ race\ group)$. The results are shown in Table 6. We observe that the results are particularly different for Hispanic as compared to American Indian and Alaskan Native, Asian Pacific Islander, Black, and White.

Despite interpreting our models, we know that there is omitted variable bias specifically with known OVB from not accounting for perception and payment methods, and unknown OVB that varies by more than year or neighborhood. This would mean that from our model, we are still unable to determine a causal relationship between fare and fare evasion both at the extensive margin and the intensive margin.

Conclusion

This paper sought to determine the effect of an increase in fares on fare evasion, particularly motivated by the circumstances surrounding the New York Subway system: distribution of income throughout the city, a change in nominal fare, and the sheer complexity that makes the subway system a part of everyday life for many people. While my paper didn't achieve any significant results, they are due to limitations that are solvable and would be valuable to look at in greater detail.

Apart from the omitted variable bias that is present in our model, we have limitations within our model from lack of variation, specifically in our main regressor: fares. We are interested in the causal effect of fares on fare evasion but the only variation in our regressor arises from considering inflation. That is, while we take into account real fares, it is entirely possible that for the everyday consumer, they are only aware of the nominal value. A possible solution to this limitation will require more data, particularly information on summons when the nominal fare was less than \$2.75 and if the nominal fare was greater than \$2.75. With this information, not only would we have greater variation across our regressor, but it might also be possible to utilize a difference in difference methodology.

Other ways to improve on the existing empirical model and actually determine the causal relationship would be solving for the OVB, either by using an instrumental variable approach or using proxies to account for the variation from our unobserved variables.

In addition to the limitations mentioned above, another limitation of my model is that aspects of the model are built on intuition rather than empirics. To address this limitation, I would need to have more background knowledge on the relationship between variables in my model.

To conclude, this paper attempted to look at the causal relationship between fare and fare evasion, looking at both the extensive margin and intensive margin and taking into account potential differences in effects experienced by people of different racial groups. Although there are no significant results, this is a starting point.

References

A Night in Jail Over \$2.75. (2019, July 29). https://theappeal.org/a-night-in-jail-over-2-75/ admin. (n.d.). Understanding the Psychology of Fare Evasion. Public Transport Research Group. Retrieved December 16, 2023, from https://publictransportresearchgroup.info/portfolio-item/understanding-the-psychology-of-fare-evasion/

American Public Transportation Association. (1991). Fare Elasticity and its Application to Forecasting Transit Demand.

http://archive.org/details/pham-linsalata-fare-elasticity-1991

Anderson, M. L. (2014). Subways, Strikes, and Slowdowns: The Impacts of Public Transit on Traffic Congestion. *American Economic Review*, 104(9), 2763–2796. https://doi.org/10.1257/aer.104.9.2763

Berger, P. (2019, June 17). MTA to Add More Officers to Subway to Stop Fare Evaders. *Wall Street Journal*.

https://www.wsj.com/articles/mta-to-add-more-officers-to-subway-to-stop-fare-evaders-11560810239

Berger, P., & Brody, L. (2019, October 21). Police Haven't Slowed New Yorkers' Subway Fare Evasion. *Wall Street Journal*.

https://www.wsj.com/articles/police-havent-slowed-new-yorkers-subway-fare-evasion-11571697440

BLS Data Viewer. (n.d.). Retrieved December 16, 2023, from https://beta.bls.gov/dataViewer/view/timeseries/CUURS12ASA0

- Consumer Price Index Historical Tables for U.S. City Average: Mid–Atlantic Information

 Office: U.S. Bureau of Labor Statistics. (n.d.). Retrieved November 21, 2023, from

 https://www.bls.gov/regions/mid-atlantic/data/consumerpriceindexhistorical_us_table.ht

 m
- Curtin, J. F. (n.d.). EFFECT OF FARES ON TRANSIT RIDING.
- Fearnley, N. (2013). Free Fares Policies: Impact on Public Transport Mode Share and Other Transport Policy Goals. *International Journal of Transportation*, *1*, 75–90. https://doi.org/10.14257/ijt.2013.1.1.05
- gloria. (2018, April 11). *The psychology behind fare evasion*. Trainsfare. https://www.trainsfare.eu/psychology-behind-fare-evasion/
- Hickey, R. L. (2005). Impact of Transit Fare Increase on Ridership and Revenue:
 Metropolitan Transportation Authority, New York City. *Transportation Research Record*, 1927(1), 239–248. https://doi.org/10.1177/0361198105192700127
- Johnson, H. C., & Richards, H. D. J. (n.d.). THE COUNCIL OF THE CITY OF NEW YORK.
- Kheel Plan: Double the Congestion Charge & Make Transit Free Streetsblog New York

 City. (2007, December 18).
 - https://nyc.streetsblog.org/2007/12/18/the-kheel-plan-double-the-congestion-charge-then-make-transit-free
- LASSOW, W. (n.d.). EFFECT OF THE FARE INCREASE OF JULY 1966 ON THE

 NUMBER OF PASSENGERS CARRIED ON THE NEW YORK CITY TRANSIT

 SYSTEM.

List of New York City Subway stations. (2023). In Wikipedia.

https://en.wikipedia.org/w/index.php?title=List_of_New_York_City_Subway_stations&oldid=1184074725

McClain, N. (2019). Caught inside the black box: Criminalization, opaque technology, and the New York subway MetroCard. *The Information Society*, 1–21.

https://doi.org/10.1080/01972243.2019.1644410

MDAT. (n.d.). Retrieved December 17, 2023, from

https://data.census.gov/mdat/#/search?ds=ACSPUMS1Y2022&vv=%2aFINCP&rv=ucgid&wt=WGTP&g=0400000US36_795P200US3604103,3604104,3604107,3604108,3
604109,3604110,3604111,3604112,3604121,3604165,3604204,3604205,3604207,3604
208,3604209,3604210,3604211,3604212,3604221,3604263,3604301,3604302,3604303
,3604304,3604305,3604306,3604307,3604308,3604309,3604310,3604311,3604312,36
04313,3604314,3604315,3604316,3604317,3604318,3604401,3604402,3604403,36044
04,3604405,3604406,3604407,3604408,3604409,3604410,3604411,3604412,3604413,
3604414

MTA: Fare and toll evasion is responsible for \$700 million a year in lost revenue - CBS New York. (2023, May 17).

https://www.cbsnews.com/newyork/news/mta-fare-toll-evasion-lost-revenue/

MTA Will Spend \$249M On New Cops to Save \$200M on Fare Evasion—Streetsblog New York City. (2019, November 14).

https://nyc.streetsblog.org/2019/11/14/mta-will-spend-249m-on-new-cops-to-save-200 m-on-fare-evasion

- New York City Subway. (2023). In *Wikipedia*.

 https://en.wikipedia.org/w/index.php?title=New_York_City_Subway&oldid=11896304

 25
- Nguyen, T. (2019, November 12). Fare evasion costs cities millions. But will cracking down on it solve anything? Vox.

 https://www.vox.com/the-goods/2019/11/12/20959914/fare-evasion-costs-cities-million
 <a href="mailto:s
- NICASTRO, J. (2023, July 19). NYC Subway Fare Hikes Are Fair. *National Review*. https://www.nationalreview.com/corner/nyc-subway-fare-hikes-are-fair/
- Parry, I. W. H., & Small, K. A. (2009). Should Urban Transit Subsidies Be Reduced? *The American Economic Review*, 99(3), 700–724.
- Passenger Transportation. (n.d.). HIGHWAY RESEARCH BOARD DIVISION OF ENGINEERING NATIONAL RESEARCH COUNCIL NATIONAL ACADEMY OF SCIENCES-NATIONAL ACADEMY OF ENGINEERING.

 https://onlinepubs.trb.org/Onlinepubs/hrr/1968/213/213.pdf
- Pinsker, J. (2015, January 29). Why Can't Public Transit Be Free? *The Atlantic*.

 https://www.theatlantic.com/business/archive/2015/01/why-cant-public-transit-be-free/384929/
- Reddy, A. V., Kuhls, J., & Lu, A. (2011). Measuring and Controlling Subway Fare Evasion:

 Improving Safety and Security at New York City Transit Authority. *Transportation*Research Record, 2216(1), 85–99. https://doi.org/10.3141/2216-10
- Reports—Subway Fare Evasion—NYPD. (n.d.). Retrieved November 20, 2023, from https://www.nyc.gov/site/nypd/stats/reports-analysis/subway-fare-evasion.page

- SPA Professors Examine Racialized Responses to Metro Fare Evasion. (2021, April 21).

 American University.
 - https://www.american.edu/spa/news/spa-professors-examine-racialized-responses-to-me tro-fare-evasion.cfm
- State of New York. (n.d.). State of New York. Retrieved December 17, 2023, from https://data.ny.gov/browse/select_dataset?nofederate=true&sortBy=relevance&suppressed_facets[]=domain&utf8=%E2%9C%93
- Subway Fare Evasion. (n.d.). Retrieved November 20, 2023, from https://metrics.mta.info/?subway/fareevasion
- The MTA's False Fare Evasion Narrative. (2020, January 29).

 https://www.cssny.org/news/entry/mta-false-fare-evasion-narrative-data
- The Real Costs of Curbing Fare Evasion. (2023, April 19). *Bloomberg.Com*.

 https://www.bloomberg.com/news/features/2023-04-19/budget-strapped-subways-get-to-ugher-on-turnstile-jumpers
- U.S. Census Bureau QuickFacts: New York city, New York; United States. (n.d.). Retrieved December 17, 2023, from
 https://www.census.gov/quickfacts/fact/table/newyorkcitynewyork,US/PST045222
- Wagner, L. (2020, January 29). Here Are the Fare-Evasion Enforcement Data the NYPD Fought to Keep Secret. *Vice*.
 - https://www.vice.com/en/article/y3mww7/here-are-the-fare-evasion-enforcement-data-t he-nypd-fought-to-keep-secret
- White, G. B. (2015, May 16). Our Struggling Public Transportation System Is Failing America's Poor. *The Atlantic*.

ublic-transportation-increases-inequality/393419/	ublic-trans	sportation-inc	creases-ineo	uality/3934	419 /		
				,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,			

Tables and Figures

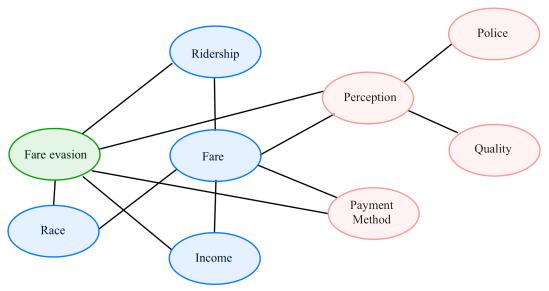


Figure 1. Ideal causal diagram looking at the effect of fare on fare evasion

Summary statistics

	N	Mean	SD	Med	Var	Skew	Kurtosis	1st Perc.	99th Perc.
Summons for ALL PERSONS	4798	40.899	95.37	9	9095.431	5.937	49.828	0	503
Real fare in 2021Q4 dollars	4798	2.91	.08	2.925	.006	541	2.333	2.75	3.03
RealAVGFamilyInc.in2021Q4\$s	4798	70675.493	38314.031	60055.035	1.468e+09	1.686	5.764	26031.145	198341.53
Ridershin	4798	2692796	3638221.7	1630405	1 324e+13	5 337	47 194	211247	18585755

Table 1. Descriptive statistics for relevant variables

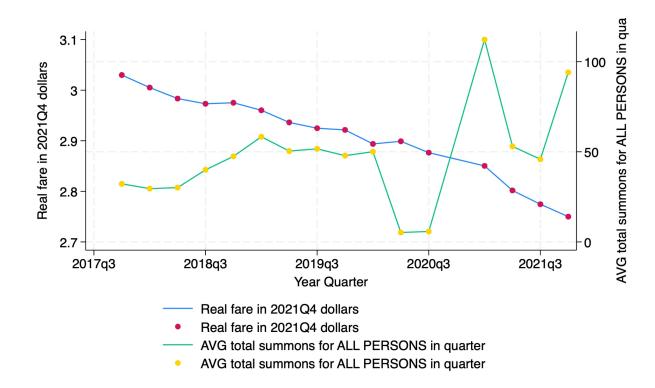


Figure 2. Real fare over time in 2021q4 dollars and average total summons for ALL persons in a quarter over time

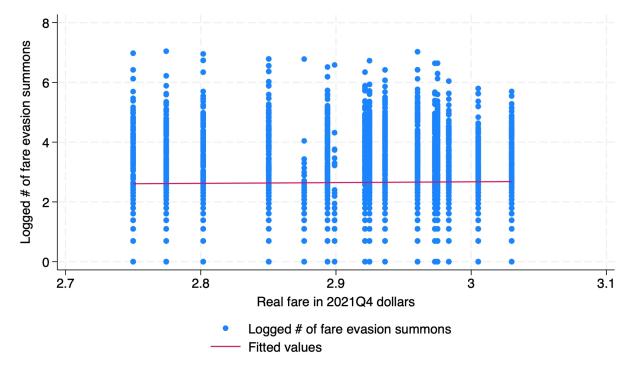


Figure 3. Relationship between Real fare in 2021Q4 dollars and Logged # of fare evasion summons

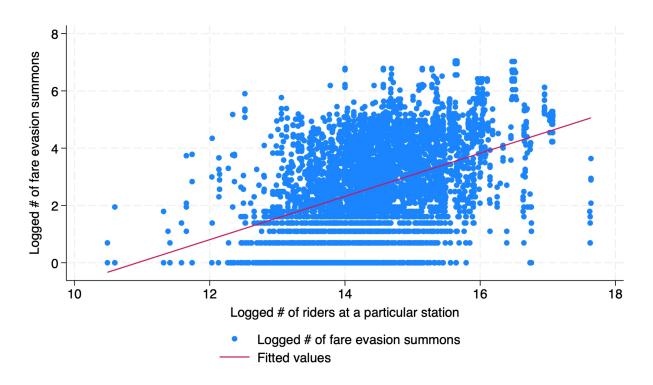


Figure 4. Relationship between Logged # of riders at a particular station and Logged # of fare evasion summons

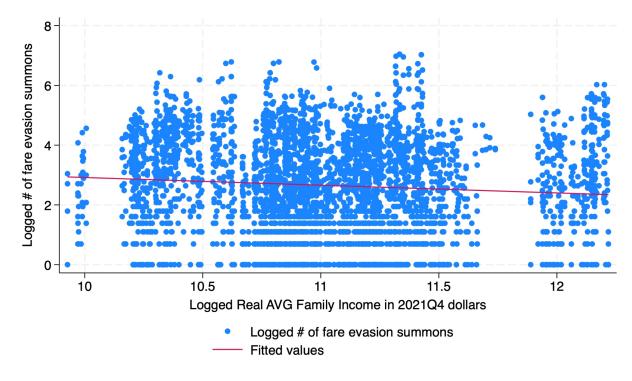


Figure 5. Relationship between Logged Real average Family income in 2021Q4 dollars and Logged # of fare evasion summons

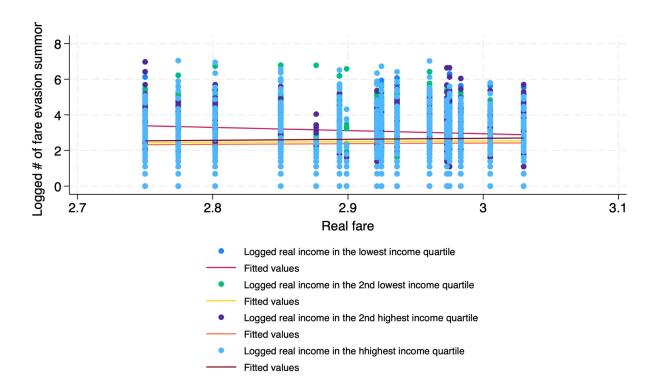


Figure 6. Relationship between Real fare in 2021Q4 dollars and Logged # of fare evasion summons by Income quartiles

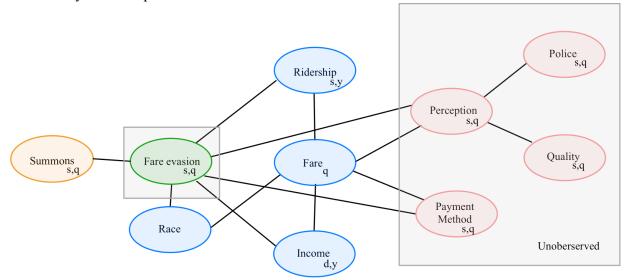


Figure 7. Causal diagram for empirical model looking at the effect of fare on fare evasion

Extensive margin **(1)** (3) **(4)** (2) Naive Preferred **VARIABLES** Naive + controls Naive model + controls + specification squared terms + model + controls interaction + squared terms + interaction + fe -0.326*** Real fare in 2021Q4 dollars 0.121* 0.889 0.032 (0.065)(0.059)(1.160)(1.069)-0.050*** Logged Real AVG Family 0.272 0.188 Income in 2021Q4 dollars (0.010)(0.308)(0.317)c.fareReal2021#c.logIncome -0.110 -0.029(0.105)(0.096)Logged # of riders at a 0.113*** 0.252** 0.307** particular station (0.006)(0.118)(0.128)SqrlogRider -0.005-0.007(0.004)(0.004)0.497*** Constant 0.731*** -3.826-3.244(0.189)(0.199)(3.427)(3.575)Observations 4,798 4,798 4,798 4,798 R-squared 0.001 0.079 0.080 0.371 Year FE YES Neighborhood FE YES

Table 2. Extensive margin

Extensive margin using LPM, Probit, and Logit

Extensive margin using Li W, 1 took, and Logic							
(1)	(2)	(3)					
Preferred	Preferred	Preferred					
specification -	specification -	specification -					
LPM	Probit	Logit					
0.032	3.136	8.785					
(1.069)	(10.153)	(19.321)					
0.188	2.137	4.791					
(0.317)	(2.967)	(5.664)					
-0.029	-0.493	-1.157					
(0.096)	(0.917)	(1.744)					
0.307**	-2.684**	-5.966***					
(0.128)	(1.115)	(2.147)					
-0.007	0.126***	0.267***					
(0.004)	(0.040)	(0.077)					
-3.244	-2.071	-6.816					
(3.575)	(33.962)	(65.113)					
4,798	4,478	4,478					
0.371							
YES	YES	YES					
YES	YES	YES					
	(1) Preferred specification - LPM 0.032 (1.069) 0.188 (0.317) -0.029 (0.096) 0.307** (0.128) -0.007 (0.004) -3.244 (3.575) 4,798 0.371 YES	(1) (2) Preferred specification - LPM Probit 0.032 3.136 (1.069) (10.153) 0.188 2.137 (0.317) (2.967) -0.029 -0.493 (0.096) (0.917) 0.307** -2.684** (0.128) (1.115) -0.007 (0.126*** (0.004) (0.040) -3.244 (2.071 (3.575) (33.962) 4,798 0.371 YES YES					

Table 3. Extensive margin using LPM, Probit, and Logit

Extensive margin given race **(1) (4)** (5) (3) (6) (2) Preferred Preferred Preferred Preferred **VARIABLES** Preferred Preferred specification specification specification specification specification specification for ALL for BLACK for WHITE for for for summons AMER IND ASIAN PA summons HISPANIC summons CIFIC ISLA ALASK NAT summons **NDER** summons summons Real fare in 2021Q4 0.032 -2.549** -1.965 0.699 0.861 -2.468dollars (1.069)(1.128)(1.883)(1.515)(1.791)(1.547)Logged Real AVG 0.188 -0.582* -0.263 0.437 0.577 -0.423Family Income in 2021Q4 dollars (0.317)(0.323)(0.545)(0.452)(0.448)(0.526)c.fareReal2021#c.logInc -0.0290.227** 0.106 -0.110 -0.1330.171 ome (0.096)(0.169)(0.160)(0.102)(0.140)(0.136)0.307** -0.554*** -0.471** 0.377** 0.370** Logged # of riders at a 0.063 particular station (0.128)(0.143)(0.184)(0.168)(0.175)(0.176)0.022*** 0.024*** SgrlogRider -0.007-0.006 -0.0060.006 (0.004)(0.005)(0.006)(0.006)(0.006)(0.006)Constant -3.244 10.044*** -6.965 -7.810 7.363 4.920 (3.575)(3.618)(6.111)(5.040)(5.029)(5.944)Observations 4,798 4,798 4,798 4,798 4,798 4,798 R-squared 0.371 0.166 0.330 0.367 0.311 0.344 Year FE YES YES YES YES YES YES YES Neighborhood FE YES YES YES YES YES

Table 4. Extensive margin using LPM across different race groups

	Intensive margins	
	(1)	(2)
VARIABLES	Preferred specification -	Robustness test on same
	model + controls + squared	model with a randomly
	terms + interaction + fe	selected half of the
		observation
Real fare in 2021Q4 dollars	-3.005	-3.274
	(5.337)	(8.076)
Logged Real AVG Family Income	0.813	0.196
in 2021Q4 dollars		
	(1.537)	(2.334)
c.fareReal2021#c.logIncome	0.019	0.078
	(0.484)	(0.730)
Logged # of riders at a particular	0.153	-0.128
station		
	(0.761)	(1.131)
SqrlogRider	0.031	0.040
	(0.026)	(0.039)
Constant	-7.807	0.282
	(17.429)	(26.538)
Observations	4,072	2,030
R-squared	0.482	0.478
Year FE	YES	YES
Neighborhood FE	YES	YES

Table 5. Intensive margin using preferred specification with robustness test

Intensive margins given race								
	(1)	(2)	(3)	(4)	(5)	(6)		
VARIABLES	Preferred	Preferred	Preferred	Preferred	Preferred	Preferred		
	specification	specification	specification	specification	specification	specification		
	for ALL	for	for	for BLACK	for	for WHITE		
	summons	AMER_IND	ASIANP	summons	HISPANIC	summons		
		_ALASK_N	ACIFIC_ISL		summons			
		AT summons	ANDER					
			summons					
Real fare in 2021Q4 dollars	-3.005	-14.682**	-9.532*	-2.399	2.413	-5.615		
	(5.337)	(5.717)	(5.274)	(5.109)	(5.083)	(5.022)		
Logged Real AVG Family	0.813	-3.758**	-1.114	0.369	2.127	-0.299		
Income in 2021Q4 dollars	373-2			0.0	_,_,			
	(1.537)	(1.739)	(1.537)	(1.493)	(1.454)	(1.435)		
c.fareReal2021#c.logIncome	0.019	1.275**	0.679	0.070	-0.456	0.361		
<u> </u>	(0.484)	(0.519)	(0.478)	(0.464)	(0.460)	(0.455)		
Logged # of riders at a	0.153	-1.489**	-2.184***	-0.734	-0.171	-1.764**		
particular station								
	(0.761)	(0.656)	(0.578)	(0.764)	(0.718)	(0.760)		
SqrlogRider	0.031	0.056**	0.087***	0.054**	0.031	0.082***		
	(0.026)	(0.022)	(0.020)	(0.026)	(0.025)	(0.026)		
Constant	-7.807	53.147***	32.455*	0.379	-18.742	17.298		
	(17.429)	(19.964)	(17.267)	(16.903)	(16.509)	(16.386)		
Observations	4,072	460	2,073	3,315	3,434	2,797		
R-squared	0.482	0.491	0.406	0.501	0.466	0.448		
Year FE	YES	YES	YES	YES	YES	YES		
Neighborhood FE	YES	YES	YES	YES	YES	YES		
	Standard errors in parentheses *** p<0.01 ** p<0.05 *p<0.1 Table 6. Intensive margin across different race groups							