Transport Policy 55 (2017) 79–86

Contents lists available at ScienceDirect

Transport Policy

journal homepage: www.elsevier.com/locate/tranpol

Does the demand response to transit fare increases vary by income?

Caroline Miller[a,1], Ian Savage[b,*]

[a] Allstate Insurance Company, 2675 Sanders Road, Northbrook, IL 60062, USA

[b] Department of Economics, Northwestern University, 2001 Sheridan Road, Evanston, IL 60208, USA

ARTICLE INFO

Keywords:
Transit
Ridership
Fares
Income
Chicago

ABSTRACT

Changes in ridership at individual stations on Chicago's mass-transit rail system following fare increases in 2004, 2006, 2009 and 2013 are analyzed to determine whether the ridership response varies with the per capita income in the neighborhood surrounding each station. We find mixed results. For one of the four fare changes the decline in ridership is greater in lower-income neighborhoods than it is in higher-income neighborhoods. However, the reverse is found for another fare increase. For two of the increases there is no relationship between income and ridership response. These mixed findings are in line with the prior literature that also found an inconsistent relationship. We hypothesize that there are two competing forces at work. On one hand lower-income groups are more constrained in their budget, but on the other hand they have fewer options for switching to other modes.

1. Introduction

When a transit agency raises its fares, does the demand change by a similar proportion in all areas of the city, or does it vary with the income or other characteristics of individual neighborhoods within the city? This is a very pertinent question in the politically-charged environment in which heavy subsidized and largely publicly-owned transit agencies operate. Most of the North American transit industry charges a flat fare so increases apply uniformly to all riders. Consequently part of the political resistance to fare increases is the concern that lower-income riders may be disproportionately affected, and that these riders rely on inexpensive transit fares for basic mobility and access to jobs.

The issue requires an empirical investigation because there are two conflicting forces at work. On one hand, riders in lower-income neighborhoods are less likely to have access to a car, meaning that they are less able to switch modes in response to a fare increase. They would therefore be less fare responsive than riders in higher-income neighborhoods with greater car access. On the other hand, lower-income riders are less able to tolerate the effects of a fare increase as it represents a greater proportion of their daily budget. This would imply that they would be more fare responsive than higher-income riders. Four recent fare increases by the Chicago Transit Authority offer an opportunity to investigate the issue. Changes in the number of riders entering at individual rail stations are analyzed with respect to the income characteristics of the neighborhoods surrounding each station.

A couple of clarifications are necessary. The first is that this paper is not concerned with whether or not people in lower-income neighborhoods ride public transportation more or less frequently than those in higher-income neighborhoods (in other words, we are not estimating an income elasticity of demand). Rather it deals with whether there are systematic variations in how residents in neighborhoods of differing income characteristics react to fare changes. The second is that our data do not permit calculation of fare elasticities per se. This is because the changes in ridership are measured over a 12-month period, and exogenous demand shocks caused by the business cycle and changing gasoline prices occurred at the same time as the changes in fares.

2. Literature review

There is a large literature on the fare elasticity of demand for public transportation (see the meta studies by Hensher, 2008; Holmgren, 2007; and Wardman, 2014). However, there has been little attention paid to investigating whether the demand response to fare changes varies between riders due to differences in their incomes. The limited prior literature is summarized in the British (Balcombe et al., 2004, at page 61) and United States (Transportation Research Board, 2004, at pages 12–36 to 12–38) practical handbooks. The latter concludes (on page 12–36) that "[t]he effect of income on fare elasticities is not well researched."

The earliest paper appears to be Lassow's (1968) analysis of a fare increase in New York City in 1966. He found that ridership declined by

* Corresponding author.
E-mail addresses: caroline.miller11@gmail.com (C. Miller), ipsavage@northwestern.edu (I. Savage).

[1] This work was conducted while a student at Northwestern University.

http://dx.doi.org/10.1016/j.tranpol.2017.01.006
Received 24 May 2016; Received in revised form 17 November 2016; Accepted 27 January 2017
Available online 12 February 2017
0967-070X/

8.6% at 10 stations in "depressed areas of the city," but by only 2.7% at stations near commuter railroad and bus terminals that were patronized by commuters of "presumably higher economic status." However, ten years later, Obinani (1977) found a contrary result after the 1975 fare increase in New York City. While in general he found "ridership reductions in roughly equal proportions from all major socioeconomic and demographic groups," there were suggestions that groups with annual household incomes of greater than $15,000 ($66,200 in 2015 dollars) were slightly more likely to change mode as a result of the fare increase. Moreover, the lowest rate of work-trip mode changes occurred among "household heads with lower incomes, having no more than a high school education, under 34 years of age, and nonwhite."

Experiments with free off-peak transit in the United States in the 1970s allowed observation of whether certain income groups were overrepresented among the generated ridership. Swan and Knight (1979) found that higher-income riders in Denver (from households with income more than $20,000, the equivalent of $78,200 in 2015 dollars) were more responsive to the fare reduction than were lower-income riders. However, further analysis of the Denver experiment by Mayworm et al. (1980) found little variation among income groups. But the latter authors did find some evidence that middle and higher-income riders (those with annual household incomes of $10,000 or more which equates to $32,600 or more in 2015 dollars) were more responsive than lower-income riders during a similar off-peak free fare experiment in Trenton, New Jersey.

Cummings et al. (1989) used both stated and revealed preference data to examine the effects of three Chicago Transit Authority fare increases in the early 1980s. For work trips, the authors found that lower-income riders (from household with incomes of less than $30,000, the equivalent of $64,800 in 2015 dollars) had slightly more fare sensitivity than higher-income riders. However, there was no difference in fare sensitivity for non-work journeys.

Mackett (1990) used a micro-analytical simulation model to estimate the fare elasticities for bus service in the British city of Leeds. He found a limited variation between the socio-economic groups, and estimated a fare elasticity of −0.67 for unskilled manual workers, −0.69 for skilled manual workers and −0.62 for non-manual workers.

Halcrow Fox and Associates (1993) found in Britain that "the greater a traveller's income, the more elastic the response to a fare increase." For mass-transit rail they concluded that for work trips the fare elasticity was −0.2 for low-income riders, −0.3 for medium-income riders and −0.5 for high-income riders. For non-work trips the fare elasticities were −0.6, −0.65 and −0.75 respectively.

Molnar and Nesheim (2011) used the 2008 National Travel Survey in Britain to estimate fare elasticities for local bus service in areas outside of London. They found that the travelers drawn from the middle three quintiles of annual household incomes (from £12,500 to £50,000, which is approximately $21,000 to $84,000 in 2015 dollars) had broadly the same fare elasticity of −0.36. Travelers in the lowest quintile of household income had a slightly more elastic demand of −0.39 and those in the highest quintile of household incomes were slight more inelastic at −0.32.

The United States practical handbook (Transportation Research Board, 2004 at page 12-7) concludes that "[t]he effect of income … is less clear, but it appears that most fare changes have affected ridership of lower income groups … less than other groups." A journal article summary (Paulley et al., 2006) of the British handbook makes a stronger statement that "[t]ravellers with high incomes tend to have higher elasticity values because their higher car ownership levels mean that they have an alternative when fares increase." This statement would certainly be consistent with the findings of Halcrow Fox and Associates (1993) for rail service. However, the results in Mackett (1990) and Molnar and Nesheim (2011) for bus services in Britain suggest that there is not a strong relationship, and that higher-income riders might actually be less fare sensitive.

3. Methodology and data

This study is an aggregate demand analysis. Aggregate analysis has advantages and disadvantages. The advantage is that transit fare increases occur reasonably frequently and therefore there is plenty of empirical data on the revealed choices of riders. The disadvantage is that unlike disaggregate demand studies (Ortúzar and Willumsen, 2011) it does not give insights into which types of people may switch modes or discontinue some trips, and their decision making process. However, while aggregate models usually miss out on the nuances of decision making, in this case the income disparities between different neighborhoods in the City of Chicago are large. The average per capita income in the areas surrounding stations varies from $10,000 a year to $75,000 a year.

3.1. Transit in Chicago

The Chicago Transit Authority (CTA) provides bus and heavy rail elevated and subway train service in the City of Chicago and inner suburbs with a fleet of 1,700 buses, and 1,000 railcars operating on eight rail routes. It services a population of 3.4 million. This analysis concerns ridership at rail stations. A similar analysis might be possible for bus services if access was available to boardings data at individual bus stops. However, publicly available data are only reported at the level of individual bus routes.

3.2. Transit fares in Chicago

The CTA single-trip pricing structure is a flat fare irrespective of distance traveled or time of day. The CTA also offers multi-day and monthly passes that can be used on both the bus and rail system. Stored-value electronic media purchased from vending machines can be used for single trips on either mode. The electronic stored-value fare media replaced pre-purchased tokens in 1999, and cash payment to an agent at a station was discontinued in 2009 (albeit the vending machines fulfill the same function). Cash can still be used to board a bus. The price of a single ride on the bus has been 25 cents cheaper than rail since 2006. Chicago does have a commuter rail system run by a separate agency that has distance-based fares. However, it generally does not serve the same markets as CTA heavy-rail service.

Since 2000 the CTA has increased its fares four times on January 1 of 2004, 2006 and 2009, and January 14, 2013. Table 1 shows the principal adult fares. The fare increases of 2004 and 2006 primarily targeted cash fares and did not change the prices for single fares and period passes paid by electronic fare media. This was at a time when the CTA was introducing electronic ticketing and wanted to encourage people to switch to this form of payment. The fare increase of 2009 eliminated the single-ride discount given to holders of the stored value

Table 1
Principal adult rail fares.

	Before 2004	2004	2006	2009	2013
Single Ride – Cash	$1.50	$1.75	$2.00	Discontinued[a]	Discontinued
Single Ride – Stored value Card	$1.36	$1.59	$1.59	$2.25	$2.25
1-day Pass	$5	$5	$5	$5.75	$10
7-day Pass	$20	$20	$20	$23	$33
30-day Pass	$75	$75	$75	$86	$100

Note:
[a] Passengers can still purchase a stored-value ticket for a single ride from a vending machine at stations.

fare media, and also increased the price of passes. The 2013 increase increased the price of passes but kept the single-ride fare the same.

The effect on average fares can be calculated by using revenue data for the CTA rail system reported to the federal government in the "National Transit Database" at https://www.transit.dot.gov/ntd and ridership data from the CTA. The average farebox revenue per person who enters the rail system increased by 12.3% from 2003 to 2004, by 20.5% from 2005 to 2006, by 11.8% from 2008 to 2009, and by 7.8% from 2012 to 2013.

3.3. Transit ridership

Data on ridership by station were obtained from the Regional Transportation Authority's[2] "Regional Transportation Asset Management System" (RTAMS) data warehouse at http://www.rtams.org. The origin of the data is a CTA publication "Monthly Ridership Report." The ridership measure is a count of passengers entering stations. Data are reported on the average ridership for weekdays, Saturdays, and Sundays/holidays for each month. The CTA publication also includes a count of the number of weekdays, Saturdays and Sundays/holidays in that particular month. Therefore one can calculate the average ridership for a weekday, Saturday and Sunday/holiday for each station and each calendar year.[3]

The dependent variable in this analysis is the ratio of the average daily ridership for the calendar year after the increase to that in the year before (a value of unity would indicate that ridership did not change). The ratio is calculated separately for the average weekday, the average Saturday, and the average Sunday / holiday. However, there is a complication in analyzing the January 1, 2009 fare increase because from March 17, 2008 the State of Illinois mandated that senior citizens could ride for free. Consequently in analyzing the 2009 fare increase, ridership in April to December of 2009 is compared with the same months in 2008.

During the period analyzed the CTA had 144 rail stations. However, 28 stations in the downtown area are excluded because boardings at these stations represent people from all parts of the city that are making trips back to their homes.[4] Also excluded are the two airport stations (O′Hare Airport on the Blue Line and Midway Airport on the Orange Line), and two stations near O′Hare (Cumberland and Rosemont) that are park and ride locations that have few residents living nearby and draw from a large catchment area. Two stations (Morgan on the Green and Pink Lines and Oakton-Skokie on the Yellow Line) did not open until mid-2012 and cannot even be included in the analysis of the 2013 fare increase.[5] This leaves 110 stations.[6]

Certain stations also had to be excluded for one or more of the fare increases because reconstruction and engineering work led to a partial closure for some months. In particular stations along the Douglas Park branch of the Blue Line (renamed the Pink Line in 2006) were excluded in both 2003-04 and 2005-06 because of major reconstruction and subsequent service enhancements. Ashland station on the Green Line was also excluded in 2005-06 as the newly-renamed and expanded Pink Line service was rerouted to serve this station from June 2006.

The Brown Line branch from Southport to Kimball was also excluded in 2005-06 and 2008-09 because individual stations were closed for extended periods for reconstruction, and passengers were advised to use neighboring stations. Consequently ridership at stations along this branch fluctuated greatly from year to year. In 2008-09 stations on the southern part of the Brown Line at Diversey and Wellington were excluded due to reconstruction, as were the neighboring stations at Fullerton and Belmont that were jointly served by the Brown and Red Lines.

An influx of capital funds in 2008-09 led to weekend reroutings and bus substitutions as engineering works dealt with a backlog of track maintenance. Consequently stations from Chicago Avenue to Harlem along the O′Hare branch of the Blue Line, plus North/Clybourn (Red Line) and Sedgwick (Brown Line) were excluded on weekends (but not weekdays) in 2008-09.

A major modernization project on the main north-south Red Line in 2012 and 2013 led to the exclusion of stations from Wilson to Howard on the north side, and from Cermak-Chinatown to 95th Street on the south side. The former saw periodic closures in the summer and fall of 2012 for modernization. The latter stations were completely closed for track renewal for five months in the summer of 2013. During this period Red Line trains were rerouted onto the neighboring Green Line. Therefore we also had to exclude all stations south of and including 35-Bronzeville-IIT station on the Green Line.

3.4. Station neighborhood income

Information on income and demographics was obtained at the census tract level from the U.S. Census Bureau's 2009 American Community Survey Five-Year Estimates. Consequently, while we have four different observations of ridership changes following the fare increases of 2004, 2006, 2009 and 2013, we only have one point observation of the neighborhood characteristics, which is for the period 2005-09.

Guerra, Cervero, and Tischler (2012) assert that a half-mile radius circle is the accepted measure in the United States to evaluate a transit station's catchment area. To create "neighborhoods" surrounding each station, an ArcGIS map of Chicago was overlaid with the location of stations and the boundaries of census tracts. A half-mile radius circle was drawn around each station. In some cases stations were close enough together that these circles intersected. In these cases a "watershed" line was drawn equidistant between each station, and the neighborhood for a given station was only that part of the circle that lay on its side of the watershed.

With these boundaries in place, the census tracts that fell either in whole or in part within each station neighborhood were identified. However, a census tract was not included if only a very small part of it fell within the neighborhood boundary. Because the station catchment area boundaries are generally circular in shape, and census tracts are generally rectangular, many of the census tracts associated with a specific station contain households that live more than 0.5 miles from the station. Therefore, the descriptive statistics of a station's neighborhood are generally based on a geographic area that is wider than just the half-mile radius circle. For each station a series of demographic variables were defined based on a weighted average of all of the census tracts that intersect the station's catchment area.

The income variable is the weighted (by population) per capita income in the census tracts. Data are collected by the Census Bureau continuously for the five years from 2005 to 2009. All responses were converted by the Census Bureau into 2009 dollars using the Consumer Price Index. Some of the previous literature used household income rather than per capita income. The correlation between the two measures for the 110 stations in the dataset was 0.94. We felt that per capita income was more appropriate in this analysis because the average household size varied significantly between the various station neighborhoods. Alternative measures of income such as the proportion

[2] The Regional Transportation Authority is the planning and financial oversight agency for public transportation in the Chicago metropolitan area, and has taxing powers to provide subsidies.

[3] The 2013 fare increase occurred on January 14 whereas the other changes occurred on January 1. This analysis treats this fare increase as if it occurred on January 1 by comparing ridership in calendar year 2013 to that in 2012.

[4] The downtown area is defined as bounded by Division Street to north, Halsted Street to the west, Roosevelt Road to the south and Lake Michigan to the east. Stations lying on the boundary are also excluded.

[5] The opening of these stations required the exclusion of the neighboring stations - Dempster on the Yellow Line and Ashland on the Green and Pink Lines – from the analysis of the 2013 fare increase.

[6] One station (Dempster on the Yellow Line) did not receive weekend service until April 2008, but analysis of weekend service at this station in 2008-09 is also excluded as ridership was in its infancy.

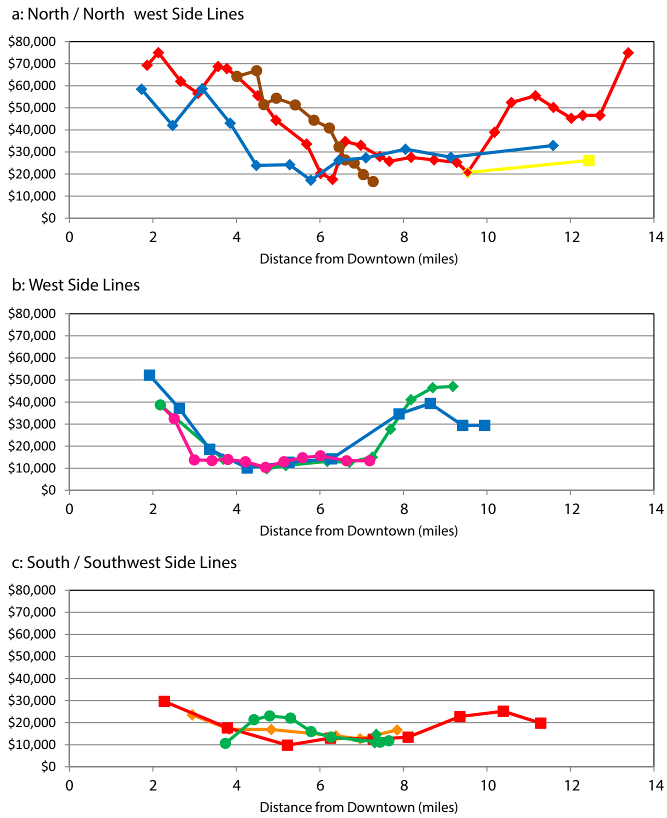

Fig. 1. Neighborhood Annual Income per Capita Versus Distance from Downtown (Lines color coded to Names used by the Chicago Transit Authority).

of the population that fell below the official poverty line, or the proportion of the working population who were unemployed were found to be both less successful as explanatory variables and highly correlated with per capita income.

We have already mentioned that there is considerable diversity in income among the station neighborhoods. The three panels of Fig. 1 graphically depict this variation. In each panel, the vertical axis is the per-capita income and the horizontal axis is the distance from downtown measured as the great circle distance between the latitude and longitude of a station and the intersection of East Lake Street and North Michigan Avenue. The latter location is equidistant from the north, west and south boundaries of the area that was used to exclude the downtown area stations (the eastern boundary is Lake Michigan).

In each panel of Fig. 1 the lines are color coded to the names of the CTA routes. The top panel shows lines on the north and northwest sides of the city, the middle panel the west side, and the lower panel the south and southwest sides. In all three panels there is a strong "U" shape with higher incomes close to downtown, then much lower incomes in the band from 4 to 8 miles from downtown, followed by rapidly rising incomes if lines enter the inner ring of suburbs. The charts illustrate the striking disparity between the relatively prosperous north side and the impoverished south and west sides.[7]

3.5. Other station neighborhood characteristics

The regression analysis used in this paper includes a measure of the population density around a station. Density is calculated by dividing the total population in the relevant census tracts by the combined area measured in square miles. Population density varies from 3,000 to 78,500 per square mile. High-density neighborhoods are often characterized as transit dependent because congestion and parking difficulties make automobile usage less desirable. The Census Bureau asks respondents about their primary mode for the journey to work, and for the 110 stations there is a positive correlation of 0.49 between population density and the use of public transportation. Interestingly, in Chicago both high and low income groups choose to live in high-density neighborhoods, and therefore the correlation between density and income is just 0.16.

A variable measuring the distance of the station from the center of Chicago was also included. The calculation of this variable was described in the previous section. As a flat fare system is used, there may be more diversion from transit for shorter trips as a result of the fare increase. On the other hand people located further from downtown could more easily respond to the fare increase by changing their trip destination to locations that are not served by transit. Rather surprisingly the distance from the center of town is uncorrelated with either population density (a correlation of −0.08) or per capita income (a correlation of 0.02).

A final set of variables measures the proportions of the population that are male, are aged 65 years or older, or are aged 14 or younger. We wanted to investigate whether there were any gender differences in the fare responsiveness, and whether the elderly (who in 2008-09 were able to ride for free[8]), or children (many of whom were riding on weekdays to and from school) had a different responsiveness. Neither gender mix nor the proportion of elderly are strongly correlated with per capita income. However, not surprisingly, increasing the proportion of children does have a negative 0.63 correlation with per capita income. The proportion of males in the neighborhood varies from 37% to 79% around a mean of 50%. The proportion of elderly varies from 3% to 29% around a mean of 10%, and the proportion of children varies from 6% to 41% around a mean of 22%.

3.6. Demand shocks other than fare

The effects of fare changes on ridership did not occur in a vacuum. In addition to fare increases which would lead to a movement *along* a demand function, there were other forces at work that also *shifted* the demand function either inwards or outwards. In particular from 2003 to 2004 increasing gas prices led to a modest shift from automobiles to transit (Nowak and Savage, 2013) and there was modest employment growth. From 2005 to 2006 the labor market was expanding and gas prices continued to increase, which one would imagine would lead to an outward shift in the demand curve. In contrast from 2008 to 2009 the demand curve likely shifted inwards as the labor market contracted during the "Great Recession," and the decline in gas prices made driving more attractive relative to transit. From 2012 to 2013 things were more stable with modest increases in employment, and stable gasoline prices.

Ridership can also change in response to changes in service frequency. Prior to 2012, service frequencies did not change substantially. The exception was for stations along the Forest Park branch of the Blue Line that benefited from a doubling of frequencies from June 2006 when the Pink Line was established (previously half of the Blue Lines trains branched off to service the Douglas Park branch which became the separate Pink Line). But in December 2012, additional trains, representing about 6% of revenue car miles, were introduced on all parts of the rail system to relieve overcrowding.

There has generally been a renaissance in usage of the rail system in Chicago in the past two decades. The strongest gains have occurred on the weekends. CTA annual traffic reports, available on the RTAMS website, show that between 2000 and 2014 Sundays and holidays rail ridership increased by 85%, Saturdays by 66%, and weekdays by "only" 27%. Reasons for this may include the transition to electronic ticketing

[7] The higher incomes at the outer ends of the Green and Blue Lines on the west side are where these lines enter the suburb of Oak Park.

[8] The free rides for seniors program was discontinued in 2011.

Table 2
Changes in factors influencing demand.
Sources: Fares – as explained in the text; total employment from U.S. Bureau of Labor Statistics "Local Area Unemployment Statistics" (http://www.bls.gov/lau/) for the Chicago-Naperville-Elgin metropolitan area; price of a gallon of regular gasoline in Chicago from by the U.S. Energy Information Administration at http://www.eia.gov/dnav/pet/pet_pri_gnd_dcus_yord_m.htm; annual revenue car miles from the U.S. Federal Transit Administration's National Transit Database.

	Fares Increased	Employment Changed	Gasoline Prices Changed	Revenue Car Miles Changed
2003–04	+12.3%	+0.7%	+17.4%	+1.2%
2005–06	+20.5%	+3.2%	+14.9%	−2.5%
2008–09	+11.8%	−4.8%	−27.7%	+1.7%
2012–13	+7.8%	+0.5%	−2.5%	+5.9%

that makes casual use of the system easier, and improved perceptions of personal safety at off-peak times.

Table 2 summarizes changes in factors (including fares) that may have influenced demand. The sources for the data are noted in the table. The implication is that favorable demand shocks might actually lead to an increase in ridership in some years despite a fare increase.

4. Initial graphical analysis

The purpose of this paper is to investigate whether the ridership changes at individual stations vary in a systematic way with the income of the surrounding neighborhood. Initial insights can be gained from Figs. 2–5 that show scatterplots between per capita income and ridership change for each station on weekdays following each of the four fare increases. To conserve space the plots for weekends are not shown. For all fare increases the ridership changes at individual stations on Saturdays and Sundays/holidays are correlated with the weekday changes at that station with correlation coefficients in the range of 0.65–0.8.

The first notable impression is that many stations show an increase in ridership despite the fare increases. Indeed in 2006 nearly all stations recorded ridership increases. Of course the explanation is that the buoyant economy led to an increased number of work trips and the run up in gasoline prices led to a modal shift from automobiles.

The second notable impression is that these graphs do not support a proposition that the ridership response varies in a consistent and clear-cut way with neighborhood income. In 2004 and 2009 there are positive correlations of +0.22 and +0.17, respectively, implying that stations in lower-income neighborhoods had a greater (negative) response. In 2006 the relationship was in the opposite direction with a correlation coefficient of −0.34. In 2013 the variables were essentially unrelated with a correlation coefficient of +0.04.

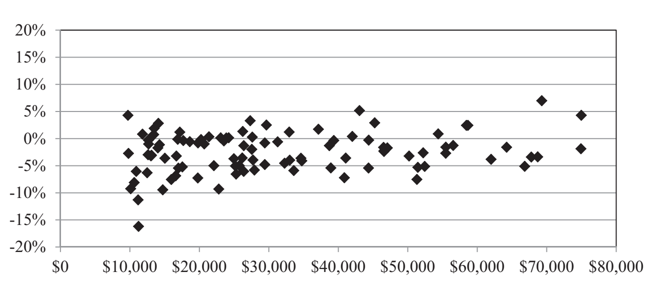

Fig. 2. Weekday ridership change versus neighborhood income per capita 2003-04.

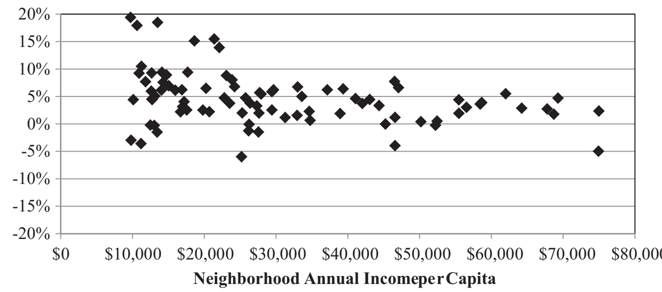

Fig. 3. Weekday ridership change versus neighborhood income per capita 2005-06.

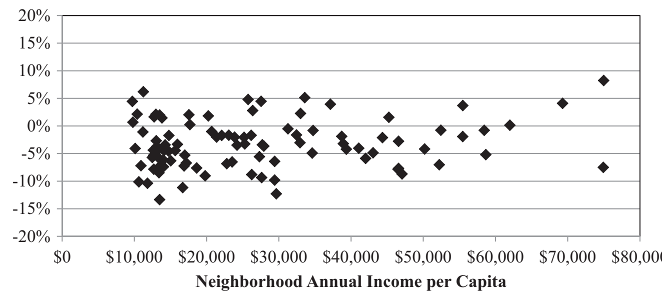

Fig. 4. Weekday ridership change versus neighborhood income per capita 2008-09.

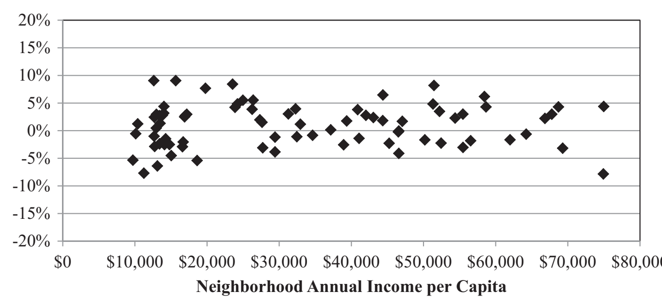

Fig. 5. Weekday ridership change versus neighborhood income per capita 2012-13.

5. Regression analysis

5.1. Pooled regressions

The initial regressions pool together the ridership changes for the four fare increases and the three types of days of the week resulting in 1043 observations. Descriptive statistics of the variables used are given in Table 3.

The first regression, the results of which are shown in the middle column of Table 4, includes fixed effects for each of the fare increases (consequently the regression was estimated without a constant term), and for each of Saturdays and Sundays / holidays (with weekdays as the base comparison). The continuous variables are expressed in logarithms. The logarithmic form was found to have marginally better explanatory power compared with a linear form.

In this regression we find no relationship at all between neighborhood income and changes in demand. But, there are other strong results. The fixed effects for weekend days are large, positive and highly statistically significant. As was been previously observed there has been a strong growth in weekend usage of the rail system in the past 15 years. We find a positive and statistically significant relationship between population density and ridership change, which would be consistent with conventional wisdom. Holding everything else constant, stations in high-density neighborhoods have a more positive (or less negative) change in ridership than similar stations in less dense neighborhoods.

We find a large and strong negative effect of distance from down-

Table 3
Descriptive statistics of variables (1043 observations).

Variable	Mean	Standard Deviation	Minimum	Maximum
Dependent Variable				
Ratio of year-over-year ridership on average day	1.02	0.06	0.81	1.19
Explanatory Variables				
Dummy variable for 2004 fare increase	0.28	0.45	0	1
Dummy variable for 2006 fare increase	0.25	0.43	0	1
Dummy variable for 2009 fare increase	0.24	0.43	0	1
Dummy variable for 2013 fare increase	0.22	0.42	0	1
Dummy variable for Saturdays	0.33	0.47	0	1
Dummy variable for Sundays / holidays	0.33	0.47	0	1
Annual per capita income in census tracts within 0.5 miles of station	$30,398	$17,579	$9,719	$74,980
Population density per square mile in census tracts within 0.5 miles of station	17,372	12,305	2,914	78,561
Distance from downtown (miles)	6.3	2.7	1.7	13.4
Proportion of males	0.50	0.05	0.37	0.79
Proportion of elderly (aged 65+)	0.10	0.05	0.03	0.29
Proportion of children (aged 0–14)	0.22	0.08	0.06	0.41
Ratio of year-over-year system-wide revenue per rider	1.13	0.05	1.08	1.20
Ratio of year-over-year total employment in Chicago region	1.00	0.03	0.95	1.03
Ratio of year-over-year price of a gallon of regular gasoline in Chicago	1.00	0.18	0.72	1.17
Ratio of year-over-year system-wide revenue car miles	1.02	0.03	0.97	1.06

Table 4
Regression results on the pooled dataset with the logarithm of the ratio of year-over-year average daily ridership as the dependent variable (t-statistics in parentheses).

Explanatory variable (continuous variables in logarithms)	Regression 1	Regression 2
Constant	-	0.005 (0.10)
Dummy variable for 2004 fare increase	0.019 (0.39)	–
Dummy variable for 2006 fare increase	0.038 (0.78)	–
Dummy variable for 2009 fare increase	0.009 (0.19)	–
Dummy variable for 2013 fare increase	0.022 (0.45)	–
Dummy variable for Saturdays	0.023 (5.74)	0.024 (5.77)
Dummy variable for Sundays / holidays	0.034 (8.48)	0.035 (8.46)
Annual per capita income	−0.001 (0.16)	0.000 (0.08)
Population density	0.007 (2.06)	0.007 (2.10)
Distance from downtown (miles)	−0.019 (4.47)	−0.019 (4.43)
Proportion of males	0.058 (3.02)	0.053 (2.76)
Proportion of elderly (aged 65+)	0.001 (0.19)	0.001 (19)
Proportion of children (aged 0–14)	0.004 (0.68)	0.003 (0.57)
Ratio of year-over-year system-wide revenue per rider	–	−0.002 (0.04)
Ratio of year-over-year total employment in Chicago region	–	−0.354 (5.31)
Adjusted R^2	0.1892	0.1017
Number of observations	1043	1043

town on ridership change. These results are consistent with some long-term trends for transit in Chicago which has seen transit strengthening its position closer to downtown and losing out on the periphery. When weekday ridership in 2014 is compared with that in 2000, stations between 1.7 and 4 miles from downtown have seen a ridership increase of 53%, those between 4 and 6 miles had a 40% increase, between 6 and 8 miles a 15% increase, between 8 and 10 miles a 5% increase, and those beyond 10 miles suffered a 10% decrease.

Somewhat surprisingly we find a positive and significant relationship between the proportion of males in a neighborhoods and ridership change. This is somewhat surprising given that the correlation coefficient between these variables is a modest 0.13. A detailed analysis of the data suggests a possible explanation. Some neighborhoods with an unusually high proportion of males are in areas on the north side about 4–6 miles from downtown that have been gentrified in the past two decades. It would seem that the urban pioneers in these regenerated areas are predominantly men. Conversely the stations with the highest proportion of females residing nearby are relatively stable areas on the south and west sides.

In contrast to the gender variable, we find that the proportion of the population that is 14 and younger or 65 and older does not seem to affect the ridership responsiveness. (The reader is reminded that this is an aggregate demand analysis at the neighborhood level and not a disaggregate model, so we are not directly analyzing the choices of people of different genders or ages).

For the fixed effects of the different fare increases, we find that the year-to-year ridership ratios are positive when the ridership variable is measured in logarithms, implying that the underlying ridership is growing over time. While the magnitude of the fixed effects varies, none are statistically significantly different from zero.

A second regression, shown in the final column of Table 4, replaced the fare increase fixed effects with a single constant term and variables resenting changes in the factors that might influence demand; the fare: gasoline prices, employment numbers, and revenue car miles as a measure of transit supply. Unfortunately not all of these variables can be used at the same time. The correlation between fares and revenue car miles is −0.97, and that between employment and gasoline prices is +0.93. Consequently, we can only use fares and employment as explanatory variables, and even these two variables have a correlation of 0.46. The resulting regression is not very satisfactory. The explanatory power is considerably worse than the first regression with the year fixed effects, and the variable measuring employment (and gasolines prices) has a counterintuitive and statistically significant negative sign. On a more positive note the coefficients on the other variables are similar to those found in the initial regression.

5.2. Analysis by day type

Further investigation revealed that fixed effects for the various days of the week are insufficient to explain the full differences. Table 5 shows the results when the first regression in Table 4 is estimated separately for weekdays, Saturdays and Sunday / holidays. The adjusted R^2 improves considerably with values that are between roughly 0.3 and 0.4. Of course, we would not expect a very high R^2 as there are many factors that could explain random fluctuations in ridership at particular stations such as neighborhood gentrification and decline, special events (festivals, concerts, a good year for a sports team), opening and closing of neighboring businesses, and street reconstruction.

We still do not find any relationship between neighborhood income and changes in demand. However, we do find additional insights into some of the other variables that were statistically significant in the regression that pooled together all day types. The large and strong negative effect of distance from downtown on ridership is found to exist

Table 5
Regression results on the logarithm of the ratio of year-over-year average day ridership by day type (t-statistics in parentheses).

Explanatory variable (continuous variables in logarithms)	Weekdays	Saturdays	Sunday / Holidays
Dummy variable for 2004 fare increase	−0.001 (0.01)	0.040 (0.49)	0.056 (0.70)
Dummy variable for 2006 fare increase	0.069 (1.10)	0.096 (1.19)	−0.013 (0.16)
Dummy variable for 2009 fare increase	−0.009 (0.15)	0.043 (0.54)	0.036 (0.46)
Dummy variable for 2013 fare increase	0.031 (0.50)	0.053 (0.66)	0.019 (0.24)
Annual per capita income	0.000 (0.07)	−0.006 (0.81)	0.006 (0.87)
Population density	0.003 (0.82)	0.012 (2.25)	0.005 (0.98)
Distance from downtown (miles)	−0.019 (3.58)	−0.021 (2.96)	−0.017 (2.45)
Proportion of males	0.033 (1.32)	0.079 (2.49)	0.064 (2.07)
Proportion of elderly (aged 65+)	−0.003 (0.47)	0.001 (0.14)	0.005 (0.65)
Proportion of children (aged 0–14)	0.002 (0.31)	0.001 (0.14)	0.010 (1.06)
Adjusted R^2	0.3861	0.2890	0.4129
Number of observations	359	342	342

and to be of a similar magnitude on all days of the week.

The positive and statistically significant relationship between population density and ridership change is found to be a Saturday phenomenon. Perhaps the high residential density neighborhoods not only have a large base of non-car-owning residents wishing to make Saturday leisure trips, but also these (primarily lakefront) neighborhoods have recreational and social activities that draw people from elsewhere in the city and have a chromic lack of parking. We also find that the positive and significant relationship between the proportion of males in a neighborhoods and ridership change is a weekend rather than a weekday phenomenon. These gentrifying neighborhoods also boast restaurants and nightlife that have attracted weekend traffic.

5.3. Analysis by individual fare increase

An additional analysis was conducted by looking at the effects of each individual fare increase. Twelve regressions were run, one for each combination of the four fare increases and the three day types. For the sake of space, we only report the regressions for weekdays in Table 6. The sign and the statistical significance of the income variable was the same on the weekend in each year as it was on weekdays. The four regressions shown in Table 6 therefore match up with the scatterplots of data in Figs. 2–5.

In 2004 there was a positive and highly statistically significant relationship between income and ridership change, implying that stations in lower-income neighborhoods have a greater (negative) response. Yet in 2006 an almost identical in magnitude and statistically significant relationship was found in the opposite direction. In 2009 and 2013 these variables were essentially unrelated.

These regressions give additional insights on the other explanatory variables. We find that the distance variable whereby transit strengthened its position closer to downtown but lost out on the periphery was a phenomenon particularly associated with the earlier increases in 2004 and 2006, and was less noticeable in 2009 and 2013.

6. Summary and policy implications

Public transit in North America operates in a very political environment. Operations are heavily subsidized. Transit planning, and in most cases transit operations, are conducted by public agencies. Among the multiple objectives of these agencies is a concern that transit should provide a base level of mobility to the least fortunate members of society who do not have access to reliable private transportation.

Flat fare pricing structures are very common. Therefore, when fares have to rise all riders experience the same increase. In public hearings and in transit board deliberations on fare increases, community activists argue that lower-income riders would be disproportionately penalized. On one level it is clearly true that lower-income riders will be hurt more than higher-income riders. A given increase in the flat fare will be more painful to those with a tighter budget constraint provided that there is a diminishing marginal utility of income.

This paper looks at another aspect of the issue. Does a fare increase lead to a greater reduction in trip making by lower-income riders compared with higher-income riders? This paper analyses changes in ridership in the year following four fare increases at 110 mass transit rail stations in Chicago that are outside of the downtown area. These stations serve neighborhoods of widely differing per capita income, with a range from $10,000 a year to $75,000 a year.

We find that the hypothesis that ridership falls more at stations in lower-income neighborhoods is only found after one of the four fare increases. The reverse relationship was found following another fare increase. In the remaining two fare increases there was essentially no relationship between the ridership change and the income in the neighborhood surrounding the station. These rather mixed results mean that one cannot make strong statements about whether ridership by lower-income riders is more or less sensitive to fare increases than is ridership by higher-income riders.

The current result is not an anomaly. A review of the prior literature finds a similar ambivalence. The studies in the United States in the 1960s and 1970s found contradictory evidence. The disaggregate

Table 6
Regression results on the logarithm of the ratio of year-over-year average weekday ridership by fare increase (t-statistics in parentheses).

Explanatory Variable (Continuous Variables in Logarithms)	2004	2006	2009	2013
Constant	−0.104 (0.99)	0.385 (3.17)	−0.192 (1.46)	0.015 (0.12)
Annual per capita income	0.027 (3.05)	−0.032 (3.15)	0.004 (0.34)	−0.005 (0.49)
Population density	−0.004 (0.56)	−0.001 (0.10)	0.013 (1.54)	0.012 (1.28)
Distance from downtown (miles)	−0.024 (2.57)	−0.027 (2.52)	−0.013 (1.23)	−0.009 (0.85)
Proportion of males	0.070 (1.56)	−0.009 (0.18)	0.021 (0.43)	0.111 (2.14)
Proportion of elderly (aged 65+)	0.010 (0.99)	−0.014 (1.22)	−0.007 (0.56)	−0.001 (0.11)
Proportion of children (aged 0–14)	0.027 (2.06)	0.000 (0.02)	−0.011 (0.69)	−0.016 (0.99)
Adjusted R^2	0.1356	0.2089	0.0663	0.1011
Number of observations	99	87	95	78

demand analysis in Chicago in the late 1980s by Cummings et al. (1989) found little differences by income group. In the United Kingdom, Mackett (1990) and Molnar and Nesheim (2011) found quite similar fare elasticities across income and socio-economic groups. The strongest contrary result was in Halcrow Fox and Associates (1993) British analysis that found that higher-income groups are more negatively responsive to fare increases, especially for rail commuting trips. This latter analysis perhaps prompted a strong statement to this effect in the review article by Paulley et al. (2006) reporting on the British handbook on public transport demand.

Perhaps we can theorize about why this paper and the prior literature have offered ambivalent and contradictory empirical evidence on ridership responsiveness. There is a balancing act and a tension between two competing forces when transit fares rise. On one hand lower-income groups are more constrained in their budget and hence might be more responsive, but on the other hand they have fewer options for switching to automobiles.

So in the public debate about the desirability of raising transit fares, one can certainly argue that lower-income riders bear more of the pain because transit fares represent a larger fraction of their disposable income than is the case for higher-income riders. But one cannot argue convincingly that lower-income riders will reduce their trip making more than higher-income riders.

References

Balcombe, Richard, et al., 2004. The Demand for Public Transport: A Practical Guide. TRL Limited, Crowthorne, UK, (Report TRL593)⟨http://www.demandforpublictransport.co.uk/⟩.

Cummings, C. Philip, et al., 1989. Market segmentation of transit fare elasticities. Transp. Q. 43 (3), 407–421.

Guerra, Erick, Cervero, Robert, Tischler, Daniel, 2012. Half-mile circle: Does it best represent transit station catchments? Transp. Res. Rec. 2276, 101–109.

Halcrow Fox and Associates, 1993. London Congestion Charging: Review and Specification of Model Elasticities. Report by Halcrow Fox and Associates, Accent Marketing Research, and the University of Leeds for the United Kingdom Department of Transport. London: U.K. Department of Transport.

Hensher, David A., 2008. Assessing systematic sources of variation in public transport elasticities: some comparative warnings. Transp. Res. Part A: Policy Pract. 42 (7), 1032–1043. http://dx.doi.org/10.1016/j.tra.2008.02.002.

Holmgren, Johan, 2007. Meta-analysis of public transport demand. Transp. Res. Part A: Policy Pract. 41 (1), 1021–1035. http://dx.doi.org/10.1016/j.tra.2007.06.003.

Lassow, William, 1968. Effect of the fare increase of July 1966 on the number of passengers carried on the New York city transit system. Highw. Res. Rec. 213, 1–7.

Mackett, Roger, 1990. Exploratory analysis of long-term travel demand and policy impacts using micro-analytical simulation. In: Peter, Jones (Ed.), Developments in Dynamic and Activity-Based Approaches to Travel Analysis. Avebury, Brookfield, VT, 384–405.

Mayworm, Patrick, Lago Armando, M., McEnroe, J. Matthew, 1980. Patronage Impacts of Changes in Transit Fares and Services. Ecosometrics Incorporated, Bethesda, MD.

Molnar, Joszef, Nesheim, Lars, 2011. A Disaggregate Analysis of Demand for Local Bus Service in Great Britain (excluding London) using the National Travel Survey. Report prepared for the UK Competition Commission. ⟨http://www.eea-esem.com/files/papers/eea-esem/2012/2382/StaticTransportModel_2011_12_15.pdf⟩.

Nowak, William P., Savage, Ian, 2013. The cross-elasticity between gasoline prices and transit use: evidence from Chicago. Transp. Policy 29, 38–45. http://dx.doi.org/10.1016/j.tranpol.2013.03.002.

Obinani Felix, C., 1977. Analysis of user response to the 1975 New York City transit-fare increase. Transp. Res. Rec. 625, 12–14.

Ortúzar, J., Willumsen, L.G., 2011. Modelling Transport 4th edition. Wiley, Chichester.

Paulley, Neil, et al., 2006. The demand for public transport: the effects of fares, quality of service, income and car ownership. Transp. Policy 13 (4), 295–306. http://dx.doi.org/10.1016/j.tranpol.2005.12.004.

Swan, Sherril, Knight, Robert, 1979. Denver Off-Peak Free Fare Public Transit Experiment. Report UMTA-CO-06-0010-79-1. U.S. Dept. of Transportation, Urban Mass Transportation Administration, Washington, DC.

Transportation Research Board, 2004. Traveler Response to System Changes, Transit Cooperative Research Project Report 95. Washington, DC: Transportation Research Board (see especially Chapter 12 Transit Pricing and Fares). ⟨http://onlinepubs.trb.org/onlinepubs/tcrp/tcrp_webdoc_12.pdf⟩.

Wardman, Mark, 2014. Price elasticities of surface travel demand: a meta-analysis of UK evidence. J. Transp. Econ. Policy 48 (3), 367–384 ⟨http://www.ingentaconnect.com/content/lse/jtep/2014/00000048/00000003/art00002⟩.