Riding More Frequently

Estimating Disaggregate Ridership Elasticity for a Large Urban Bus Transit Network

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Stop-level transit elasticities with respect to service frequency are estimated and discussed. Public transportation ridership is typically studied at an aggregate level, with variables influencing ridership averaged over time and space for a metropolitan area. Understanding transit ridership at a finer temporal and spatial level is generally limited to mode choice models. Most aggregate analyses are unable to capture important effects at the parcel or block level. Such analyses also cannot account for variation in demand over time of day, an issue that has been addressed to some extent by time series modeling. Data for the Chicago, Illinois, transit system were used, and results suggest that aggregate analyses overestimate the effect of service frequency on demand. In the context of other disaggregate analyses, these findings suggest that walking quality results in distinct increases in ridership, even after accounting for land use and for population and other demographics. A headway elasticity of ridership was estimated to be −0.263 to −0.277, very similar to recent disaggregate analysis of New York City transit data. The case is made for a better spatiotemporal understanding of transit ridership for the effective allocation of resources.

As a substitute for automobile travel, public transportation reduces urban congestion and pollution, provides access to job opportunities, and provides personal mobility to groups that may otherwise be homebound (*1*). These benefits come at a cost, however, and volatility in fuel prices (and policies and funding) means that operations and maintenance budgets need to be carefully allocated to ensure a high level of service for the maximum number of riders. Factors that influence transit ridership at an aggregate level have been studied for decades (*2–4*), but these aggregate influences provide relatively little guidance to a transit agency looking to most effectively allocate resources over time and space in its particular metropolitan area. This paper describes an estimation of disaggregate transit ridership elasticities at more than 11,000 bus stops in Chicago, Illinois, for use in a bus frequency allocation model.

A primary concern of transit operators is attracting car drivers to public transit. In that sense, comfort and convenience of public transport are critical. Car users enjoy the flexibility of driving, and standing on a crowded bus for an hour is typically not preferred to driving alone or with a friend in comfort for 40 min. Thus, setting bus frequencies with appropriate ridership elasticities (and effective crowding constraints) can mean more comfort across the system, as bus frequencies will be adjusted to serve demand where it exists. Understanding how demand varies over time and space allows operators to meet the demand with supply, rather than letting demand follow supply (*5*).

Following a review of the factors that influence transit ridership, there is a description of the data used to estimate medium-term and longer-term elasticities with respect to service frequency for the Chicago Transit Authority (CTA) bus network in Illinois. An elasticity model is estimated using average daily boardings by stop and half hour. Results of the model suggest that several insights gained from aggregate transit ridership elasticity estimation are also applicable to disaggregated behavior, while others should be examined in greater depth for individual agencies. Note empirical confirmation that some less commonly used measures, such as walkability (the suitability for walking), seem to explain a significant degree of variation in transit ridership. Results indicate that headway elasticity of ridership was −0.277 in the medium term and −0.263 in the longer term, lower even than the typical values reported by aggregate ridership studies, which range from −0.3 to −0.9 (*3, 4, 6*). Ridership elasticity with respect to headway is in line with that found recently for a disaggregate analysis of New York City: the ridership elasticity with respect to vehicle revenue miles was 0.27. These findings show the need for agencies to examine unique characteristics of their service area, to identify sectors that may be underserved, and to offer opportunities to better serve new and existing riders.

BACKGROUND REVIEW

Many factors influence the demand for transit directly and indirectly. Direct effects are those relating to the quality of transit service, while indirect effects influence other uses of other modes (e.g., fuel prices and land use). The former are largely under the control of the transit agency (internal), while the latter are often outside its control (external). Table 1 characterizes these factors as described in the literature (*3, 5, 6*).

External, indirect effects are often used to understand aggregate transit ridership to forecast demand over time or for a new system. Researchers find issue with such aggregate estimates because these aggregates do not allow for evaluation of specific attributes of unique transit systems, such as personal safety, schedule reliability, or parking supply and cost (*6*). These aggregates also fail to distinguish between short- and long-run effects.

Direct, internal effects influence individual riders' choices and are often studied to inform transit agencies where to allocate resources. Direct, external effects are more difficult to capture; thus, few studies

TABLE 1 Factors Influencing Individual and Aggregate Transit Ridership

Factor	Direct	Indirect
Internal	Transit fare, frequency and span of service, comfort, speed, cleanliness, reliability	Operator funds
External	Dwell time, reliability, convenience, walk quality, traveler attitudes, safety, security, gasoline prices as influence on transit fare, travel time between origin–destination pairs	Land use density and mix, parking prices and supply, income, car ownership, nonmotorized modes, employment and population characteristics, gasoline prices as influence to use other modes

of the impact of these attributes on transit ridership exist. In particular, factors influencing awareness of and attitudes toward transit service are difficult to measure or apply in models. The variables of focus for this study span all three categories (other than internal indirect) described in Table 1.

Recently, researchers have thoroughly examined some external factors that influence aggregate transit ridership (*6, 7*). Taylor et al. use two-stage simultaneous equation regression models of data from 265 U.S. urbanized areas (*6*). This method is intended to measure the influence of transit supply on demand to examine variation in transit ridership across cities. Variables identified as having the most influence were area of urbanization; population and population density; regional location; income; car ownership; and share of non–transit and non–single occupancy vehicle trips (carpools, walking, and biking). The number of college students, immigrants, and Democratic voters were also significant. Thompson et al. used linear regression and found similar variables to be significant in determining transit ridership in Atlanta, Georgia (*7*). In addition, Thompson et al. found that travel time between origin zone and destination zone had the greatest influence on transit ridership (*7*). However, out-of-vehicle travel time, and whether the origin or destination was a transit-oriented development (TOD) were much less significant overall. Indicators for TODs and the central business district were important for rail ridership; these effects may otherwise have been captured through proxies such as population and employment. Thompson et al. suspect that mixed land use, walkability, and treatment and price of parking are what set these TODs apart from others in the study area (*7*). Thus, variables such as walk quality and land use, though external, may have a significant influence on transit ridership, and they should be explored in further depth.

Chen et al. (*5*) use New York City transit data to explore the relationship between supply and demand beyond the work of Taylor et al. (*6*) by exploring asymmetries and lagged effect. Autoregressive models of order 1, or AR(1) models of transit use over time, demonstrate that ridership responds more to increases than to decreases in gas prices. Chen et al. point out that microlevel demand estimation has few implications for large-scale understanding of transit ridership, but macrolevel views ignore the fact that population and employment of a region shift the transit demand curve (*5*). The study confirms that demand follows supply and suggests that long-run elasticities are needed to capture lagged responses to direct and indirect effects. These long-run elasticities are also more significant than short-run elasticities. An understanding of the interaction between

supply and demand of transit over different time horizons is needed to allocate transit resources appropriately.

There is currently limited understanding of how bus frequency influences ridership directly at a disaggregate level at different times of the day. Ridership tends to be more responsive to bus frequency changes than to fare changes and fuel costs (*8, 9*). Furthermore, off-peak riders are normally more sensitive than peak riders to such changes. Despite this stronger response, ridership elasticity with respect to fare and fuel costs are more frequently reported (*3–5*). However, frequency and headway elasticities can often be inflated: without cross elasticities, which would account for competition with other routes and modes, it is difficult to identify whether users enter or leave the transit market or simply switch routes (*3, 9*). Models need to be as sensitive as are the riders in a transit network, to provide useful recommendations to policy makers and operators.

The analysis described in this paper builds on the work of others by estimating ridership elasticity with respect to a broad range of spatial and temporal attributes.

DATA

The CTA implemented across the board bus service changes, primarily reductions, in February 2010. Ridership data from the months of October 2009, May 2010, and October 2010 were used to capture elasticity while minimizing effects owing to seasonal variation. These months were chosen because the weather and ridership patterns are roughly similar in each. The data available consisted of monthly average boardings and alightings for each bus stop in the network by route and half hour. Thus, records consisted of route, direction, half hour, stop, boardings, alightings, and headway information for each stop (roughly 300,000 route, stop, and half-hour combinations depending on the month and year). Stops where the absolute change in ridership or headway was less than 5% or greater than 150% were filtered from the data to eliminate extreme values.

The Chicago Metropolitan Agency for Planning (CMAP) makes available disaggregate land use and demographic data (*10*). Each CTA stop was assigned to the appropriate CMAP subzone—an area of .25 mi^2 (.64 km^2)—and thus joined to population, crime, and employment data for that subzone. Land use data were available at a finer parcel level for the year 2005. Population data come from the 2010 census, crime data from the City of Chicago data portal (*11*), and employment data from the Illinois Department of Employment Security (*12*).

Walk Score is an increasingly popular measure of a location's walkability, suitability for walking. With the use of the free Walk Score application programming interface (*13*) and the longitude and latitude of CTA bus stops, each stop was assigned a Walk Score between 1 and 100 as defined by the Walk Score creators:

- 0 to 24: car-dependent, almost all errands require a car;
- 25 to 49: car-dependent, a few amenities within walking distance;
- 50 to 69: somewhat walkable, some amenities within walking distance;
- 70 to 89: very walkable, most errands can be accomplished on foot; and
- 90 to 100: walker's paradise, daily errands do not require a car.

To compute a Walk Score, points are awarded based on the distance to amenities by categories; "amenities within .25 miles

receive maximum points, and no points are awarded for amenities further than one mile" (*13*).

Supply of competing and complementary modes was also considered. If a CTA bus stop was within 100 m of an urban rail (CTA rail), commuter rail (Metra), or suburban bus (Pace) stop or station, appropriate indicators were assigned using shape files.

Fare data were not included in the work presented here because fare cost did not change across the periods examined. However, from January 2008 to September 1, 2011, seniors (older than age 65) were eligible to ride free, so this may influence the age parameter. Fare type could also be included; this data item is available at the route level and may be included in future work.

Similarly, fuel costs were not initially included in this model since the focus of the reported study was to explore ridership elasticities as related to mostly direct individual effects. Rises in fuel costs are assumed to have a greater impact on rail ridership than bus ridership, and they are more pertinent to models involving mode switching. However, changing fuel costs between October 2009 and October 2010 will be incorporated into future models.

METHODOLOGY

To estimate variation in transit demand at the stop level for a 30-min interval of a day, several model structures were explored; the most appropriate resulting model was a log-log model. Elasticity (*E*) is the ratio of a percentage change in some variable (*X*) in response to a percentage change in another variable (*Y*), all else equal:

$$\frac{dE(Y|X)}{dX}\frac{x}{E(Y|X)} = \frac{\partial \ln E(Y|X)}{\partial \ln X}$$

When the change in *X* is infinitesimally small, elasticity can be approximated as

$$\frac{\partial \ln E(Y|X)}{\partial \ln X} \approx \frac{\%\Delta Y}{\%\Delta X}$$

Estimating a linear relationship between the log of boardings at a stop and the log of headway—and other sociodemographic variables—directly yields arc elasticities. The model is specified as

$$\ln\left(b_{t,r,s}^{v}\right) = \alpha + \beta_h \ln\left(h_{t,r,s}^{v}\right) + \beta_e \ln\left(b_{t,r,s}^{v-1}\right) + \beta_{\varpi} \ln\left(\varpi_s\right)$$

$$+ \left[\sum_{\varphi \in \Phi}\sum_{z \in Z}\beta_{\varphi} \ln\left(Y_{\varphi,z}\right)X_s^z\right] + \left[\sum_{a \in A}\lambda_a X_s^a\right] + \left[\sum_{\mu \in M}\lambda_{\mu} X_{t,s}^{\mu}\right]$$

$$+ \left[\sum_{u \in U}\lambda_u X_t^u\right] + \varepsilon_{t,r,s}^{v} \qquad t \in T, r \in R, s \in S, v \in V$$

where

    A = set of land use categories;
    a = subscript for land use category, $a \in A$;
    Φ = set of sociodemographic categories;
    φ = subscript for sociodemographic category, $\varphi \in \Phi$;
    M = set of modes (urban rail, commuter rail, suburban transit);
    μ = subscript for mode, $\mu \in M$;
    U = set of time of days [owl (midnight to 5 a.m.), a.m. peak, midday, p.m. peak, evening];
    u = subscript for time of day, $u \in U$;

    V = set of periods;
    v = superscript denoting period, $v \in V$ (*v*–1 = October 2009, *v* = May 2010 for medium term and October 2010 for longer term);
    Z = set of zones;
    z = subscript for zone, $z \in Z$;
    α = intercept;
    $b_{t,r,s}^{v}$ = number of boardings at stop *s* at half hour *t* belonging to directed route *r* during period *v*;
    $h_{t,r,s}^{v}$ = headway at stop *s* at half hour *t* belonging to directed route *r* during period *v*;
    ϖ_s = Walk Score of stop *s*;
    $Y_{\varphi,z}$ = value of sociodemographic category φ in zone *z*;
    X_s^a = binary indicator of stop *s* belonging to land use category *a*;
    $X_{t,s}^{\mu}$ = binary indicator of mode μ's existence at stop *s* at half hour *t*;
    X_t^u = binary indicator of half hour *t* belonging to time of day *u*;
    X_s^z = binary indicator of stop *s* belonging to zone *z*;
    λ_a = parameter associated with land use category *a*;
    λ_{μ} = parameter associated with mode μ;
    λ_u = parameter associated with time of day *u*;
    β_e = term to capture influence of boardings $b_{t,r,s}^{v-1}$ during period *v* − 1, a lagged dependent variable;
    β_h = ridership elasticity with respect to headway $h_{t,r,s}^{v}$;
    β_{φ} = ridership elasticity with respect to sociodemographic category value $Y_{\varphi,z}$;
    β_{ϖ} = ridership elasticity with respect to Walk Score ϖ_s;
    T = set of half hours;
    R = set of routes; and
    $\varepsilon_{t,r,s}^{v}$ = error term for stop *s* at half hour *t* belonging to directed route *r* during period *v*.

One key benefit of disaggregate stop-level elasticity estimation is that it overcomes the inflation that may be caused by aggregating route or network ridership, or both. When ridership is aggregated, users switching routes can cause overall ridership changes to be small (*9*). Initial models included indicators for every route, to capture their idiosyncratic nature; once relevant explanatory variables were identified, however, these route indicators were removed from subsequent models so that the results could be transferable. For more on the effects of such indicators, readers are referred to detailed sensitivity analysis of these elasticities (*14*).

In preparing the data to estimate this model, there was no explicit coupling of stops in one direction with their corresponding stop in the other direction. That is, boardings at a given stop in the morning peak period were neither compared with nor constrained by alightings at the stop across the street in any evening period. Origin–destination pairs were not considered, so the data reflect unlinked boardings rather than linked trips.

Furthermore, these elasticities do not reflect any information about origin–destination pairs, or even origins or destinations, so there may perhaps be a ceiling based on the possible riders. For example, if 1,000 people are already boarding at some stop in a half hour, there is no constraint that the headway elasticity could not be −0.8, suggesting that reducing headway by 50% would increase boardings by 40%, even if it seems improbable that 1,400 people could board at that stop. Thus, some stops may have a latent maximum potential ridership that is not observed.

Notwithstanding these limitations in the data, this methodology extends the work of others by including the presence of other modes, an indicator of transit supply as well as competition, land

use, and walk quality. Also, it provides valuable insight into the effect of these factors on ridership.

RESULTS

Results of the models for medium- and longer-run elasticities are described in Table 2. Somewhat surprising, the magnitudes of most effects are quite similar across the medium and longer term, although their significance varies. Results essentially corroborate those of past research, but a few key differences emerge to offer insight into spatially and temporally disaggregated transit ridership. The estimated model predicts boardings for unlinked trips, so including origin–destination data and measures of network connectivity could alter the model substantially.

The dynamic term—ln(Boardings in October 2009), included to reflect past demand—is by far the most significant variable and suggests that a number of unobserved factors are influencing the demand and elasticity of demand. Of course, this is not surprising, for certain stops will serve a unique ridership (e.g., those around major commuter rail stations or popular tourist destinations). The head-

way elasticity of ridership is estimated with very high confidence to be −0.277 in the medium term and −0.263 in the longer term. In all models, these values ranged from roughly −0.24 to −0.31, so it was surprising that in the final model they were so similar across both time horizons. However, these values are nearly identical to those from disaggregate analysis of New York City transit; ridership elasticity with respect to bus service, measured by vehicle revenue miles, was found to be 0.27 in New York City (5). This value is substantially less than those reported from aggregate studies; these values tend to be between 0.3 to 0.9 when frequency or hours per miles of service is used or −0.4 to −0.9 when headways is used (3, 4, 6, 9). These differences in magnitude suggest aggregate elasticity may be overestimating the influence of service on transit demand, at least in mature transit markets such as New York and Chicago.

The availability of urban rail within 100 m of a bus stop is also significant, and the effect is much stronger in the longer term (−0.197) than in the medium term (−0.086). The effect of rail on bus ridership is negative, perhaps a suggestion that people are more likely to transfer from bus to rail than from rail to bus. Commuter rail located within 100 m of the stop had less influence (0.054 and 0.060), but the effect is positive, possibly suggesting transfers from commuter

TABLE 2 Model Predicting Natural Logarithm of Boardings in Period 2

Explanatory Variable	Medium Term (May 2010)[a]		Longer Term (Oct. 2010)[b]	
	Estimate	t-Stat	Estimate	t-Stat
(Intercept)	−0.983	−19.56	−0.996	−18.85
ln(boardings in October 2009)	1.069	798.38	1.084	770.59
ln(headway in period 2)	−0.277	−52.26	−0.263	−46.71
CTA rail	−0.086	−6.77	−0.197	−14.72
Metra rail	0.054	3.05	0.060	3.24
Time period				
Base: noon–3 p.m.				
Time: 5–6 a.m.	−0.181	−17.36	−0.287	−26.18
Time: 6–9 a.m.	−0.083	−14.37	−0.119	−19.61
Time: 9 a.m.–noon	−0.012	−2.25	−0.014	−2.54
Time: 3–5 p.m.	−0.085	−13.15	−0.119	−17.50
Time: 5–7 p.m.	−0.139	−21.54	−0.125	−18.57
Time: 7–10 p.m.	−0.009	−1.21	−0.079	−10.16
Land use				
Construction–vacant	−0.003	−0.17	0.036	2.30
Education	−0.052	−4.03	0.082	5.98
Industrial	−0.035	−2.78	−0.049	−3.71
Medical	0.089	4.81	0.137	7.01
Mixed without parking	0.050	4.40	0.078	6.49
Mixed with parking	0.036	3.37	0.081	7.24
Other	0.041	3.29	0.068	5.19
Recreation	0.053	4.14	0.071	5.28
Residential	−0.015	−1.40	0.020	1.82
Road–utilities	−0.059	−4.85	−0.016	−1.28
Walk score	0.210	18.76	0.255	21.71
CMAP subzone characteristics				
ln(number of vehicles)	−0.001	−1.44	−0.005	−6.07
ln(crimes (2006–2009))	0.066	33.45	0.044	21.31
ln(population younger than 17 years old)	0.032	10.97	0.035	11.63
ln(population 18–64)	−0.027	−8.29	−0.025	−7.20
ln(population 65+)	0.009	4.76	−0.001	−0.70
ln(retail employment)	0.002	1.87	0.003	1.94
ln(nonretail employment)	−0.009	−8.08	−0.010	−8.21

NOTE: t-stat = t-statistic; RSE = relative standard error.
[a]RSE = 0.682; R^2 = .892; adjusted R^2 = .892; F-statistic = 54,490,000.0.
[b]RSE = 0.780; R^2 = .826; adjusted R^2 = .826; F-statistic = 28,980.0.

rail to the CTA bus. Suburban bus service was not significant. Transit users may consider urban rail as an alternative or substitute for urban bus, while the other modes are supplements to urban bus travel. The low significance of commuter rail, compared with the effect of CTA rail, suggests that the systems could be better integrated, to capitalize on proximity to one another and facilitate transfers.

Time periods were determined by grouping half hours with similar effect as determined by a fully dummied model of all half hours. The resulting time periods and their effects have several implications for service provision. As with many other transit agencies, CTA defines service by the following time periods: midnight to 5 a.m., owl; 5 to 9 a.m., AM peak; 9 a.m. to 3 p.m., midday; 3 to 7 p.m., PM peak; and 7 p.m. to midnight, evening. Some of these periods were split when the fully dummied model suggested certain hours had distinct ridership patterns from those with which they are grouped. However, ridership elasticity with respect to time of day could stem from the fact that service provision is dictated by these half hours. Two main insights stand out. First, the 5 to 6 a.m. hour is significantly more elastic than the remainder of the peak period (−0.181 versus −0.083 in medium term; −0.287 versus −0.119 in longer term). Second, in the medium term, the second half (5 to 7 p.m., −0.139) of what the CTA refers to as the PM peak is quite different from the first half (3 to 5 p.m., −0.085). Over the longer term, however, the PM peak elasticity of ridership is similar across both halves. In general, peak period ridership is considered less elastic than off-peak ridership (3, 4), but these values suggest that certain segments of the peak may be quite different. Further exploration of demand over time of day by time of year is justified, since these differences could result from the amount of daylight

or number of students in school during May as compared with October. Sensitivity analysis to assess the importance of these time-of-day effects is discussed in Verbas et al. (14), with an optimization model that incorporates these factors in service planning and frequency allocation (15).

Nearly all land uses were significant at the 1% level (*t*-value 2.576) or better, but the magnitudes are small in both the medium and longer terms. Other built environment or neighborhood characteristics may be more appropriate explanatory variables. In spite of this, educational and medical land uses stand out. That the medium-term elasticity of ridership is more negative when the land use is education (−0.052) likely is because some schools in Chicago end in mid- to late-May, so there would be fewer riders toward the end of the month, meaning the monthly average stop boardings used to estimate elasticities are lower than those observed in October. This could also explain the difference in the medium term and longer term of stops in residential parcels. When the stop is located near a clinic, hospital, nursing home, or other health care facility, the ridership increase is significantly higher: 0.089 in the medium term and 0.137 in the longer term. This suggests that transit agencies should pay particular attention to these land uses in allocating service. To better illustrate the implications of land use on ridership elasticity, Figure 1 illustrates the median medium-term elasticity for each land use class over the course of 24 h. In general, elasticities are less stable over the course of the day for industrial, medical, recreational, and educational areas than for the other land uses. In future models, single family and multifamily residential uses could be separated, and the number of vehicles could be interacted with residential land use.
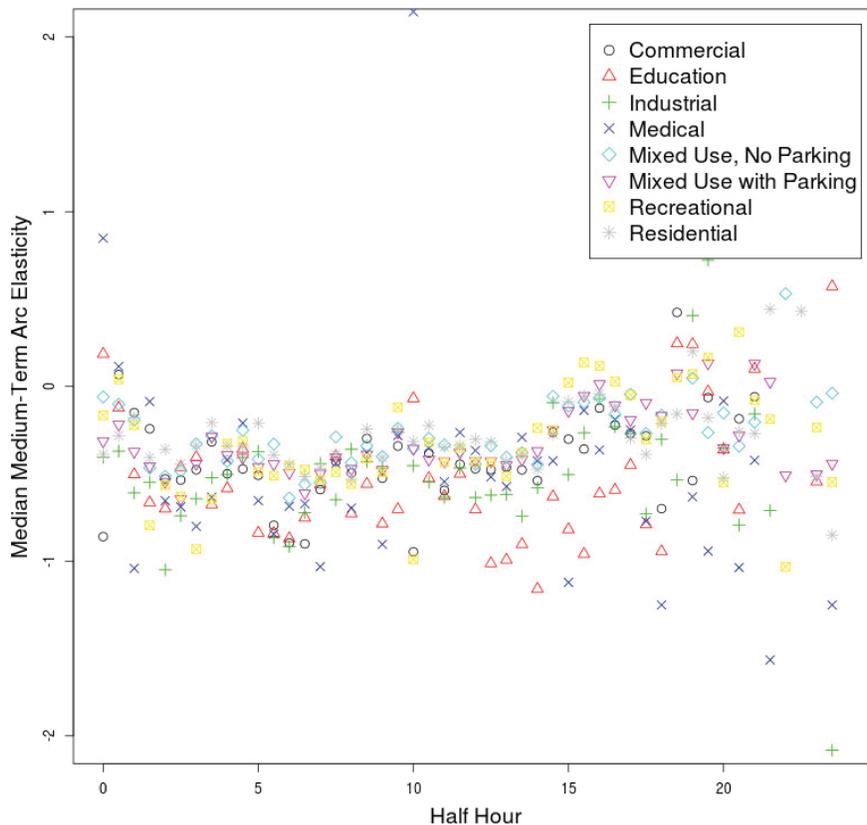

FIGURE 1   Median medium-term elasticity over 24 h, by land use category.

The relative significance and magnitude of the Walk Score may account for the similar magnitudes of land uses. A 1% increase in Walk Score predicts a 0.21% increase in ridership in the medium term and 0.25% increase in the longer term. This supports the concept that neighborhood design and density encourage transit use, and specifically that distance to amenities could be more important than mixed land use alone. Of course, these Walk Scores are based on the surrounding neighborhood, while land use is based only on the parcel. Furthermore, Walk Score may be acting as proxy for the convenience of transit, so Transit Score (a measure of transit access provided by the same company) could be included as well. Walk Score and Transit Score may also explain why some TODs were significant trip producers and attractors in Atlanta while others were not (*7*). In any case, quality and convenience and access to transit emerge as very important variables toward understanding disaggregate transit ridership.

Finally, sociodemographic characteristics of the zone in which the stop is located are important for explaining disaggregate ridership elasticity, but some of the magnitudes reported here disagree with findings from both disaggregate and aggregate transit ridership studies. Kain and Liu found that a 1% increase in employment in a metropolitan area would result in a .25% increase in overall transit ridership (*2*). Chen et al. found that an increase in employment would lead to no increase in ridership in the short term, but a .59% increase in the longer term (*5*). In contrast, the model presented here suggests much smaller increases in ridership as retail employment increases (0.002 and 0.003, medium term and longer term, respectively). It also suggests that ridership decreases as nonretail employment increases (−0.009 and −0.010, but this effect is only significant at the 10% level, much less than other variables here). Of course, this and other effects could result from the nature of the model, which predicts unlinked boardings, not overall network ridership.

Studies typically report that increases in population and population density increase transit ridership (*2, 6*). However, as Taylor et al. (*6*) pointed out, the characteristics of that population are important. Table 2 shows that a larger population of individuals younger than 17 years old predicts higher ridership, and this effect is similar across both time horizons (0.032 and 0.035). However, the number of residents age 18 to 64 has the opposite effect; ridership tends to decrease as this proportion of the population increases (−0.27 and −0.25).

Vehicle ownership, while a good predictor of aggregate transit ridership and significant, does not explain stop level boardings as much as expected. A 1% increase in vehicle ownership results in −0.001% and −0.005% decreases in medium-term and longer-term ridership, respectively. Income should be included to understand this effect better. Ridership is also quite sensitive to the number of crimes committed in the zone between 2006 and 2009; ridership increases with crime rate by .066% in the medium term and .044% in the longer term. That points to a need to capture zonal income and crime simultaneously, for this effect is likely a result of higher transit ridership in areas with a captive transit market.

borhood design and zone level demographics affect ridership quite significantly.

Overall, the model results suggest that several insights gained from aggregate transit ridership elasticity estimation are also applicable to disaggregate behavior, while others should be examined in greater depth for individual agencies. There are also some less common measures, such as Walk Score and crime; they explain a significant amount of variation in transit ridership.

The headway elasticity of ridership was consistently estimated to be between −0.25 and −0.31 in a variety of models tested. In the final model, headway elasticity was −0.277 in the medium term and −0.263 in the longer term, lower even than the lowest typical value reported by aggregate ridership studies (*3, 4, 6*) but similar to a disaggregate analysis of New York City (*5*).

The presence of other modes within 100 m of the bus stop was highly significant, and more so for urban rail (which is integrated with the urban bus) than for commuter rail or suburban bus, or both. Boardings were slightly lower at stops with urban rail than without, probably owing to the sheer number of passengers who board at the 97% of stops that are outside that catchment area. This finding could also suggest that a larger number of passengers are transferring from bus to rail than vice versa. If a bus stop is within 100 m of commuter rail, boardings tend to be slightly higher, possibly because of the number of commuters transferring to a CTA bus from a train station to complete the last mile into the central business district.

The best explanatory predictors for disaggregate transit ridership seem to be headway, peak versus off-peak travel time, Walk Score, crime rate, and population and employment characteristics.

Further specification, including additional variables, may be investigated in future work. Income at the subzone, or at least census tract, level should be considered to better understand captive ridership. Cross elasticities that reflect competing routes are also needed to understand how ridership may shift in the network following service changes. Understanding how users substitute routes when level of service is adjusted has important implications for network reliability, and aggregate estimation of cross elasticities for competing modes can create artificially inelastic values for transit ridership. Such analysis would benefit from detailed origin–destination data.

CTA began introducing transit tracking systems in late 2009, so routes and stops for which prediction information is available may have seen increases across the time horizons analyzed here. Differences in magnitude and significance of time of day indicators also point to the need to better understand transit demand over the course of the day and time of year. Measuring parking supply and pricing, and their effect on alightings, would also be valuable.

The effect of reliability on these elasticities, and the reverse relationship, cannot be ignored. The number of passengers wishing to board affects dwell time and crowding, and thus schedule reliability. By explicitly accounting for demand in bus frequency setting, the comfort and reliability of the system may be increased. In the end, only those elements of reliability within the control of transit operators can be managed.

CONCLUSIONS

Factors influencing stop level transit boardings were examined and compared with those of past studies. The comparison studies primarily dealt with aggregate transit data, and thus some surprising results emerged at the disaggregate level. Several of these results point to a greater need to understand disaggregate transit demand, for neigh-

ACKNOWLEDGMENTS

cussions regarding the CMAP subzone demographic data. The work has benefited from suggestions and feedback provided by Joseph Schofer and Breton Johnson. Several researchers at the Northwestern University Transportation Center, including Hamed Alibabai, Raymond Chan, Andreas Frei, and Omer Verbas, have contributed to the overall study.

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