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Report No. UT-17.19

COVERAGE VS FREQUENCY: IS SPATIAL COVERAGE OR TEMPORAL FREQUENCY MORE IMPACTFUL ON TRANSIT RIDERSHIP?

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DISCLAIMER

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16. Abstract

Transit ridership has long been studied, and the findings are concisely elucidated by Taylor & Fink (2003) when they say "To sum, transit ridership is largely, though not completely, a product of factors outside the control of transit managers." While studies repeatedly examine the effects on ridership of common variables like gasoline price and fare price, few have looked with much scrutiny at the factors that are, in fact, within the capacity of transit agencies to control. Transit service provision has been found to affect ridership, but "service provision" is often nebulously defined, shedding little light onto how transit managers can best provide service that will create returns in the form of transit ridership. This study examines the effects of spatial coverage and temporal frequency on transit ridership to determine just which lever is most effective. We use a cross-sectional study design with 157 regions around the United States. We employ structural equation modeling (SEM) to explain complex relationships that exist between interrelated variables. We find that both factors are strong predictors of transit ridership, with service frequency having a slightly larger impact.

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LIST OF ACRONYMS

FHWA	Federal Highway Administration
UDOT	Utah Department of Transportation
SEM	Structural Equation Modeling
VMT	Vehicle Miles Traveled

EXECUTIVE SUMMARY

Much of the literature on transit ridership admits that the majority of the factors influencing transit ridership are outside the control of transit managers. The two determinants of ridership that are, in fact, within the power of transit agencies to control are fare price and service provision. Unfortunately, up until this point, service provision has been defined ambiguously and with a variety of different measures. Measures such as vehicle revenue hours or vehicle revenue miles are an aggregate of two important, distinct aspects of transit service provision: spatial coverage and temporal frequency.

Transit service planners have long wondered whether it is more effective, in terms of increasing ridership, to provide higher frequency at the expense of route coverage, or if the alternative produces better results. This study employs a cross-sectional design examining 157 diverse regions around the United States. Structural Equation Modeling (SEM) is used to represent the complex relationships which influence transit ridership. This is the first study to use SEM to explain transit ridership, utilizing improved measures of the built environment and transit ridership. Ridership is measured as the natural log of unlinked passenger trips per capita. Spatial coverage is measured by route density. This measure is the most appropriate for a study of this scope and design as the controls are aggregated in a similar way. Temporal frequency is measured by the average frequency of all system routes within the transit network(s) of each region.

We find that both transit frequency and route density are very impactful on ridership, with frequency having a slightly larger effect. The elasticity of transit ridership per capita with respect of transit frequency is 1.175. The elasticity of transit ridership per capita with respect to route density is 0.947. Both elasticities are high, one indeed suggesting an elastic relationship and one close behind. Both are obviously necessary to maximize transit ridership, but of the two, transit frequency seems to have a slightly greater impact on ridership.

1.0 INTRODUCTION

1.1 Problem Statement

Transit agencies are confronted with the difficult task of utilizing limited operating budgets in an attempt to offer the most useful and convenient service for their customers. Transit ridership can be considered a measurement of their effectiveness in achieving this goal, as the assignment of routes in the most optimized fashion will generate the most convenient service for customers. This, in turn, should promote improved ridership for agencies because transit service will be able to better compete with other modes like automobile travel.

The transit ridership literature has highlighted the challenge that agencies face of doing what they can with limited resources. The conventional wisdom of the relationships affecting ridership is that the majority of the factors that are most impactful on ridership are actually outside of the control of transit agencies. While a recent study has challenged this understanding (Lyons & Tian, 2017), the fact that the patronage of transit service by its customers is largely due to extraneous circumstances offers further headache to agencies that wish to grow their ridership.

1.2 Objectives

There is relative consensus that there are two levers in the hands of transit managers that can be employed to improve ridership. These are fare price and service provision. While fare price has long been identified and is the most commonly cited determinant of ridership in literature, service provision is a relatively ambiguous term. There are many facets of service provision, and in some cases, with constrained operating budgets, the manipulation of one element might require a reciprocal, inverse change in another. Transit route coverage is measured in a number of ways by transit agencies, but it roughly represents the spatial extent of a transit system. Transit service frequency is the frequency with which transit vehicles depart from a specific stop on a specific line. When more vehicles and operator hours are dedicated to increasing frequency on a high-performing line, certeris paribus, those vehicles and hours are taken from another line. This can come in the form of reduced frequencies on alternative lines, or even the elimination of lines all together. Service planners need to know what the consequences will be, in terms of ridership, if they decide to favor either frequency at the expense of coverage, or vice versa.

1.3 Scope

This study examines 157 unique regions around the US. Data were compiled from a litany of sources including the National Transit Database, the US Census' LEHD on the Map, the American Community Survey, and other sources. Transit data were linked with geographic and economic data for each region to create a rich database. A cross-sectional study design was used, looking at many regions at a single point in time. A threshold of 200,000 population was used based on the assumption that smaller regions would not have generalizable relationships between the chosen variables and transit ridership, and might not even have developed transit systems.

Structural Equation Modeling was used to explain the complex interrelated relationships that are at play in determining travel behavior at the aggregate level. Recommendations are made to suggest optimal service provision models. Specific guidelines for the geographic distribution of transit service is omitted, as the data and measures used do not describe the configuration of transit systems.

1.4 Outline of Report

This report includes the following sections:

- Introduction
- Literature Review
- Research Methods
- Results
- Conclusions
- Recommendations and Implementation

2.0 LITERATURE REVIEW

A relatively rich literature exists on the factors influencing transit ridership. More than thirty distinct factors have been identified, which can be considered both a blessing and a curse for those interested in developing a nuanced understanding of transit performance. Because of the large number of different variables on the table, as well as the variety of research methods and scope, there exists little to no consensus on universal relationships between established variables and transit ridership.

Taylor and Fink (2003) argue that the majority of the determinants of ridership are outside of the control of agency managers. Of the dozens of researched determinants of ridership, the following are outside their control: gasoline price (Lee, Han, & Lee, 2009; Haire & Machemehl, 2007; Lane, 2010; Taylor et al., 2009; Agthe & Billings, 1978; Gkritza, Karlaftis, & Mannering, 2011; Wang & Skinner, 1984; Currie & Phung, 2007; Dargay & Hanly, 1999; Syed & Khan, 2000; Taylor & Fink, 2003; Cervero, 1994); income (Gkritza, Karlaftis, & Mannering, 2011; Wang & Skinner, 1984); immigrants (Gkritza, Karlaftis, & Mannering, 2011; Wang & Skinner, 1984); and car-less households (Gkritza, Karlaftis, & Mannering, 2011; Wang & Skinner, 1984). Variables within the control of transit operators have also been studied, including fare price (Lee, Han, & Lee, 2009; Haire & Machemehl, 2007; Lane, 2010; Taylor et al., 2009; Agthe & Billings, 1978 Gkritza, Karlaftis, & Mannering, 2011; Wang & Skinner, 1984; Currie & Phung, 2007; Dargay & Hanly, 1999; Syed & Khan, 2000; Taylor & Fink, 2003; Cervero, 1994); transit-service frequency (Gkritza, Karlaftis, & Mannering, 2011; Belmonte, 2014); service information, service reliability, and other service characteristics (Taylor et al., 2009; Dargay & Hanly, 1999; Syed & Khan, 2000; Chiang, Russell, & Urban, 2011; Gkritza, Karlaftis, & Mannering, 2011; Currie & Phung, 2007; Taylor & Fink, 2003; Litman, 2004),. Typically, service provision is measured as revenue miles, which is an aggregate measure of both the geographic extent of a transit system as well as the frequency of vehicles on routes. Service provision has even been measured more vaguely, in terms of operating budgets. (Chiang, Russell, & Urban, 2011)

It is interesting to note that with more than thirty identified factors, only seven have been identified more than once. The remaining large number of variables, which have only been discussed singularly, suggests inconsistencies in study design and scope that leads to a relatively nebulous understanding of the determinants of transit ridership.

Beyond transit operators' salaries and fleet and facilities maintenance, transit agencies' operating budgets are mostly defined by a balance of service frequency and route distribution or density. Which of these two elements of transit service are most impactful on ridership? In the current study, we answer this question.

A particular source of confusion for students of transit ridership is that the methods used by researchers of the topic have been quite varied in their geographic scope, study design, and statistical methods. Both longitudinal and cross sectional study designs have been employed, each with their own respective abilities at determining particular relationships. For example, longitudinal studies have the ability to identify changing prices, demographic shifts, and alterations to service can impact ridership in the short run. (Lane, 2010) On the other hand, studies which utilize a cross sectional design are necessary for determining how demographics, built environment characteristics, and transit system characteristics impact ridership in the long run since urban areas have had decades to reach a sort of equilibrium state. (Taylor et al., 2009)

A select few transit ridership studies have employed advanced statistical methods such as neural network analysis and ARIMA models, but the status quo remains regression analysis. (Lane, 2010; Taylor et al., 2009; Belmonte, 2014; Chiang, Russell, & Urban, 2011; Gkritza, Karlaftis, & Mannering, 2011) Regression analysis is a powerful tool but it has serious limitations. Specifically, regression is unable account for the interrelated nature of complex phenomena. Within the context of a complex conceptual framework, variables can be both independent and dependent, rather than one or the other as in linear regression analysis. These mediating variables, on the causal pathways between the independent variables and dependent variable of ultimate interest, affect the dependent variable and are affected by other independent variables. Also, variables can have bi-directional causal relationships to one another, while linear regression assumes that relationships are strictly one way. These problems are addressed with structural equation modeling (SEM), a method that has so far not been utilized in the study of transit ridership. We use SEM in this study.

3.0 RESEARCH METHODS

3.1 Overview

This paper uses a cross sectional study design to determine the relative importance of spatial coverage and temporal frequency in affecting transit ridership.

3.2 Data and Variables

A database was compiled by the authors including built environmental factors, transit agency and system characteristics, demographic information, economic factors, roadway system elements, and other factors for large urbanized areas throughout the US. Consistent with Hamidi and Ewing (2014) and Ewing et al. (2017), we limited our sample to urbanized areas with populations of 200,000 or more for which all variables in Table 1 could be estimated. Of the 173 urbanized areas with populations of 200,000 or more, some cases were lost for lack of density metrics, others for lack of transit data, and still others for lack of fuel price data. The rationale for limiting our sample to larger urban areas is that small areas are different qualitatively than large areas. We wanted a more homogenous sample. It is spurious to compare a transit system in a large area like Los Angeles (population 12.6 million, where trips are long, congestion is intolerable, and transit is ubiquitous) to a transit system in a small area like Porterville, CA (population 79 thousand, where trips are necessarily short, congestion is nonexistent, and transit is minimal). Our final sample consists of 157 urbanized areas.

Data come from a variety of sources including the National Transit Database, Federal Highway Administration (FHWA) *Highway Statistics*, US Census, American Community Survey, National Transit Database, and other sources. The database was originally compiled by the authors for previously published papers on VMT growth and traffic congestion but has been supplemented with additional data for the purpose of this inquiry. (Ewing et al., 2014; Ewing et al., 2017a; and Ewing et al., 2017b) The specific variables used in the structural equation model are described in Table 1.

TABLE 1 SEM Model Variables

Variable	Definition	Source
Exogenous Variables		
Fuel	Natural log of regional fuel price	US Energy Information Administration
Pop	Natural log of population	US Census, American Community Survey
Inc	Natural log of median income	American Community Survey
Olm	Natural log of other lane miles (roadway miles, non-freev	Federal Highway Administration, Highway Statistics
Flm	Natural lof of freeway lane miles	Federal Highway Administration, Highway Statistics
Endogenous Variables		
Popden	Natural log of population density	American Community Survey
Rtden	Natural log of transit system route density	National Transit Database
Tfreq	Natural log of average transit fequency (headways)	National Transit Database
Outcome Variable		
UnlkdPsTrps	Natural log of unlinked passenger trips per capita	National Transit Database

Our outcome variable, natural log of unlinked passenger trips per capita, is an improvement over typical aggregate measures of transit ridership. Most often, studies use annual boardings as the dependent variable, which depends on area size. By presenting ridership on a per capita basis, we control for the confounding influence of area size. Endogenous variables, which are variables affected by other variables within a system or model, include population density, route density, and service frequency. Exogenous variables, whose values are determined outside the system of equations, include fuel price, population, income, other lane miles, and freeway lane miles. For simplification, these variables are assumed to be functions of external forces only.

3.2.1 Data and Variables Logarithmic Transformation

All variables were transformed by taking natural logarithms. The use of logarithms has two advantages. First, it makes relationships among our variables more nearly linear and reduces the influence of outliers (such as New York and Los Angeles). Second, it allows us to interpret parameter estimates as elasticities, which summarize relationships in an understandable and transferable form.

3.2.2 Data and Variables Elasticities

An elasticity, a term most commonly used in economics, describes how the change in one variable can be used to predict the change in another. For example, if gasoline price has an elasticity of 0.5 with respect to transit ridership, a 10% increase in gasoline price could be expected to produce a 5% increase in transit ridership. An elasticity of 0.5 represents a positive, "inelastic" relationship. In economic terms, a relationship is considered inelastic when a change in the independent variable produces a lesser change in the dependent variable. Within the context of the ridership literature, most previously identified relationships can be considered inelastic by this definition. However, when these relationships are viewed in aggregate, they can collectively have a major impact on ridership.

3.3 MODELING

Structural Equation Modeling (SEM) was used for this study in order to accurately represent the complexity of relationships of variables affecting transit ridership. Structural equation modeling (SEM) is a statistical methodology for evaluating complex hypotheses involving multiple, interacting variables. SEM is a 'model centered' methodology that seeks to evaluate theoretically justified models against data. The SEM approach is based on the modern statistical view that theoretically based models, when they can be justified on scientific grounds, provide more useful interpretations than conventional methods that simply seek to reject the 'null hypothesis' of no effect.

3.3.1 Structural Equation Modeling (SEM)

There are several related and distinctive features of SEM. In SEM:

- Hypothesized path models are evaluated based on a priori knowledge about the processes under investigation using all available information.

- The investigator tests the degree to which the structure of one or more models is consistent with the structure inherent in the data. Many models that might be envisioned commonly are rejected because they are inconsistent with the data.

- Probability statements about the model are reversed from those associated with null hypotheses. Probability values (p-values) used in statistics are measures of the degree to which the data are unexpected, given the hypothesis being tested. In null hypothesis testing, a finding of a p-value <0.05 indicates that we can reject the null hypothesis because the data are very unlikely to come from a random process. In SEM, we seek a model that has a large p-value (>0.05) because that indicates that the data are not unlikely given that model (that is, the data are consistent with the model).

- Different processes operating in systems are distinguished by decomposing relationships into direct and indirect pathways. Pathways can, thus, be either simple or compound, depending on whether they pass through other variables or not. The total effect of one factor on another is the cumulative impact summed over all the pathways connecting the two factors.

- The estimation of structural equation (SE) models involves solving a set of equations. There is an equation for each "response" or "endogenous" variable in the network. Variables that are solely predictors of other variables are termed "influences" or "exogenous" variables. Typically, solution procedures for SE models focus on the observed versus model-implied correlations in the data. The unstandardized correlations or co-variances are the raw material for the analyses. Models are automatically compared to a "saturated" model (one that allows all variables to inter-correlate), and this comparison allows the analysis to discover missing pathways and, thereby, reject inconsistent models.

In this analysis, data first were examined for frequency distributions and simple bivariate relationships, especially for linearity. To equalize and stabilize variances, improve linearity, and still allow ready interpretations, all variables were log transformed. As already noted, the resulting coefficients from modeling data transformed in this way can be interpreted as elasticities.

3.3.2 Software

The AMOS software package was used in conjunction with SPSS to generate the model. AMOS software produces a graphical representation, also known as a path diagram, of theoretical relationships that are tested empirically by the model. Straight unidirectional arrows represent causal pathways, and curvilinear bidirectional arrows represent correlations between variables. Endogenous and outcome variables have error terms that are represented by circles directly above the variable in the diagram. SEM models are evaluated based on a number of goodness of fit measures, the primary being the chi-square statistic. Inverse to traditional hypothesis testing like regression modeling, with SEM we seek a low chi-square and a high p value. A low chi-square and high p-value indicate that the data are not unlikely given the model, or the data are consistent with the model. (23)

3.4 Summary

We use structural equation modeling (SEM) which is a model-centric statistical tool to explain the complex relationships involved in estimating transit ridership. Theoretical models are tested against real data and evaluated based upon how the data fit the model. SEM is a preferred method when testing complex hypotheses that have both endogenous and exogenous explanatory variables. AMOS software is used which tests the models and provides graphics that can depict the relationships visually.

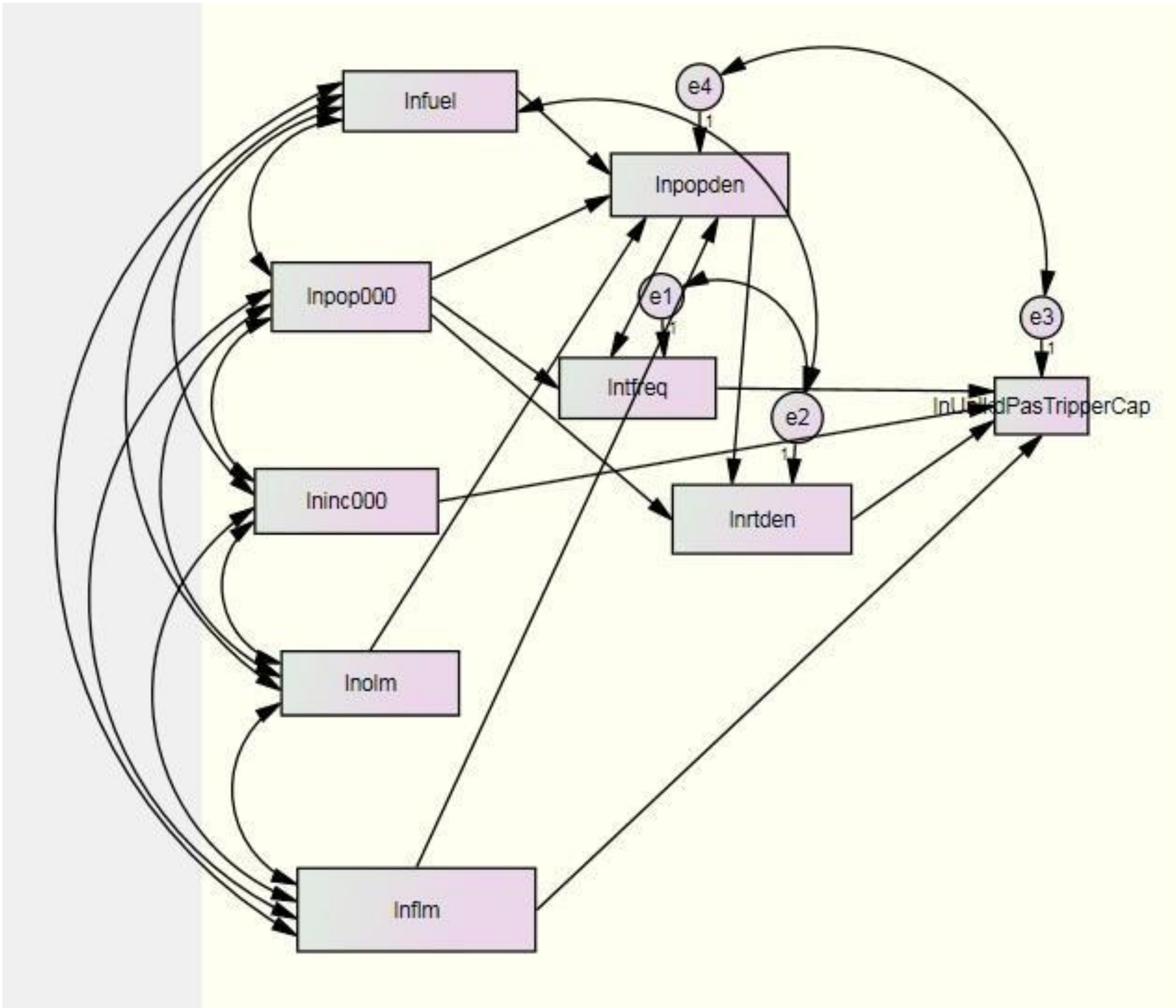
4.0 RESULTS

4.1 Overview

The model in Figure 1 has a chi-square of 14.4, with 11 model degrees of freedom and a p-value of .211. The low chi-square relative to model degrees of freedom, as well as the high p-value indicate good model fit. Additionally, other goodness of fit measures produce promising results. The root mean square error of approximation (RMSEA) of .045 falls below the conventional threshold of .05, indicating good model fit. (Browne & Cudeck, 1993) Finally, the comparative fit index (CFI) of .996 lies comfortably close to that measure's optimum value of 1. All pertinent goodness of fit measures indicate this model fits the data well. Below, Figure 1 depicts the path diagram produced by the AMOS software.

4.2 Path Diagram

FIGURE 1 SEM Path Diagram



4.2.1 Interpreting Path Diagram

Figure 1 illustrates a path diagram with exogenous variables impacting unlinked transit passenger trips per capita (ridership) both directly, and indirectly through mediating variables. For example, the diagram can be interpreted as indicating that fuel price affects population density, which, in turn, influences route density and frequency, both of which directly affect the outcome variable. Given the relative complexity of the model, we will not describe the remaining causal and correlation paths represented in the path diagram.

4.3 Causal Path Coefficients

Good model fit must also be accompanied by estimates that make theoretical sense. Table 2 includes path coefficient estimates which give the predicted effects of individual variables, ceteris paribus.

TABLE 2 SEM Path Coefficient Estimates

			Estimate	S.E.	C.R.	P	Label
lnpopden	<---	lnpop000	.139	.020	6.834	***	
lnpopden	<---	lnflm	-.178	.049	-3.651	***	
lnpopden	<---	lnfuel	1.407	.363	3.879	***	
lnpopden	<---	lnolm	-.676	.081	-8.377	***	
lntfreq	<---	lnpop000	.243	.044	5.476	***	
lnrtden	<---	lnpop000	-.095	.049	-1.926	.054	
lnrtden	<---	lnpopden	1.379	.113	12.199	***	
lntfreq	<---	lnpopden	.270	.102	2.660	.008	
lnUnlkdPasTripperCap	<---	lninc000	.511	.178	2.862	.004	
lnUnlkdPasTripperCap	<---	lnflm	.278	.092	3.025	.002	
lnUnlkdPasTripperCap	<---	lntfreq	1.175	.063	18.602	***	
lnUnlkdPasTripperCap	<---	lnrtden	.947	.055	17.330	***	

4.3.1 Path Coefficient Discussion

All of the path coefficient estimates in Table 2 are significant, with the exception of population on route density. This causal path was retained in the model for its theoretical significance.

It should be noted here that the two variables of most interest in this study, are shown in table two to be significant and highly impactful on transit ridership. Because all variables used in the model were log-transformed, the estimates in the table can be read as elasticities. The elasticity of transit ridership per capita with respect of transit frequency is 1.175. The elasticity of transit ridership per capita with respect to route density is 0.947. Both elasticities are high, one indeed suggesting an elastic relationship and one close behind. Both are obviously necessary to maximize transit ridership. But of the two, transit frequency seems to have a slightly greater impact on ridership.

4.3.2 Direct, Indirect, and Total Effects

Table 3 includes the direct, indirect, and total effects of each variable (exogenous and endogenous) on the outcome variable.

TABLE 3 SEM Indirect, Direct, and Total Effects

Variable	Effect		
	Direct	*Indirect*	*Total*
Olm	-	-1.097	-1.097
Fuel	-	2.285	2.285
Flm	0.278	-0.288	-0.01
Inc	0.511	-	0.511
Pop	-	0.422	0.422
Popden	-	1.624	1.624
Rtden	0.947	-	0.947
Tfreq	1.175	-	1.175

The indirect effects of each variable in the model on the endogenous and outcome variables are described in Table 4. The total effect on the outcome variable is the sum of the indirect effects through the endogenous variables (population density, route density, and transit frequency) plus the direct effect.

4.3.3 Total Effects on Endogenous and Outcome Variables

TABLE 4 SEM Total Effects on Endogenous and Outcome Variables

Total Effects (Group number 1 - Default model)

	lnolm	lnfuel	lnflm	lninc000	lnpop000	lnpopden	lnrtden	lntfreq
lnpopden	-.676	1.407	-.178	.000	.139	.000	.000	.000
lnrtden	-.931	1.941	-.245	.000	.097	1.379	.000	.000
lntfreq	-.182	.380	-.048	.000	.280	.270	.000	.000
lnUnlkdPasTripperCap	-1.097	2.285	-.010	.511	.422	1.624	.947	1.175

As for the other variables, Table 4 indicates that other lane miles per 1000 population has a negative effect on ridership through its impact on population density, which in turn affects route density, and service frequency. Fuel price increases ridership through a positive effect on all three endogenous variables. Freeway lane miles show small negative impacts on the endogenous variables which are mostly negated by a positive direct effect. Income only directly affects ridership, and does not interact with the endogenous variables in our model. Population has a positive total effect on ridership through its indirect effects on population density, route density, and frequency. Population density is highly impactful on route density, positively affecting ridership mostly through this variable. Again, route density and frequency both positively impact ridership, with route density having a larger effect.

4.4 Summary

The results indicate that temporal frequency is more impactful on ridership than spatial coverage. Transit ridership demonstrates an elasticity of 0.947 with respect to route density and an elasticity of 1.175 with respect to frequency.

5.0 CONCLUSIONS

5.1 Overview

Despite the general concession by researchers and transit agencies that many of the determinants of transit ridership are beyond the control of transit managers, we find that in fact, there are effective levers in the hands for transit service planners. This study indicates that temporal frequency and spatial coverage are both highly impactful on transit ridership, with frequency demonstrating a stronger impact on ridership. The difference in elasticities of these two variables, however should not be overstated. The elasticity of route density with respect to ridership is 0.947, and the elasticity of service frequency is 1.175. This represents a discrepancy in elasticities of just under 20%. Transit service planners can use these figures to better allocate service in a manner that will produce returns in ridership.

The fact that transit ridership is more responsive to frequency than coverage has real implications for the way that service planners should design transit systems. As stated earlier in the study, service planners seek to strike a balance between coverage and frequency, attempting to find a happy medium with frequent service in the core routes, and adequate route coverage throughout the rest of the service area. With this new finding, however, it appears that it would be prudent for service planners to offer increased frequency on core routes, even at the cost of sacrificing other routes. This would mean a concentration of resources into high-performing core routes, likely within more urban environments with high population and employment densities.

6.0 RECOMMENDATIONS IMPLEMENTATION

6.1 Recommendations

There are two important recommendations that are borne out of this research: 1) For the purpose of increasing transit ridership it is worthwhile for transit managers to sacrifice spatial coverage for the sake of increasing service frequency. And 2) It is important for transit managers to consider the consequences that might come from eliminating routes or reducing their extent for the purpose of increasing total system ridership.

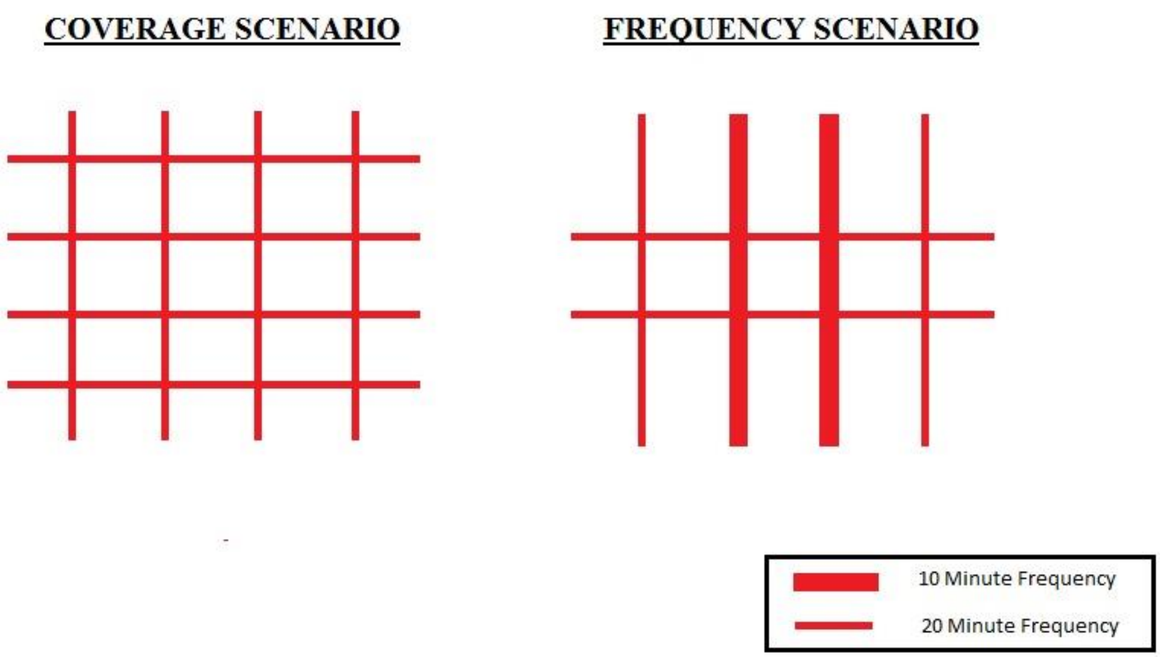
6.1.1 Increasing Frequency at the Cost of Coverage

It is inescapable that ridership is the gold standard of performance evaluation of transit agencies. A transit agency's success year over year is measured in terms of ridership, and it is this figure that dictates funds from the Federal Transit Administration and other sources. It is imperative, then, that agencies employ any reasonable means to improve ridership. As has been stated many times prior in this report, most of the literature regarding the determinants of transit ridership argues that the majority of the factors influencing ridership are outside of the control of transit agencies. Service provision, however, is a factor which has been repeatedly cited as an effective way to influence ridership. Which element of service provision is most effective in spurring increased ridership?

When considering transit system characteristics, there are many regional geographic factors that influence the spatial distribution of a system. The roadway system determines possible bus routes, and the interactions between the built environment and transportation create a dynamic demand for travel. For this reason, the measures used in this study needed to be aggregate and straightforward in nature. Route density, therefore, is the best way to measure spatial coverage of a transit system in this context. Route density describes the amount of spatial coverage of a transit system while controlling for the size of the region.

Transit service planners who read this report will leave being confident that it is better, in terms of ridership, to focus resources on high-performing at the cost of sacrificing spatial coverage. This means that it is better to have a concentrated transit system that serves the highest volume areas with the greatest observed demand with high service frequency than it is to have a system that is more widely distributed. Below, Figure 2 depicts two different service planning scenarios.

FIGURE 2 Service Planning Scenarios



In Figure 2, we see two hypothetical service planning scenarios. The left hand scenario depicts a transit system with uniform 20 minute frequency distributed on a dense grid pattern of transit routes. This is a transit system with greater route density but lower frequency. The right hand scenario depicts a similar grid-like system where two routes have been eliminated in order to furnish two of the remaining routes with increased frequency. This is a transit system with greater service frequency but lower route density. The models described in the results section suggest that the frequency scenario would perform better in terms of ridership. It is important to note that the alignment of high frequency routes is arbitrary in this context, and this study does not attempt to prescribe route alignment practices.

6.1.2 Other Service Considerations

The caveat that these service suggestions are beneficial with the specific intent of improving ridership alone cannot be overstated. Sacrificing coverage for frequency, without further consideration, is a decision that would be advisable only if ridership is the only concern of the transit agency. In this section we suggest that ridership should not be the only concern of transit agencies.

Transit managers must also consider regulations that govern the allocation of transit service, like the Federal Transit Administration's Title VI. Title VI mandates that transit agencies perform an analysis of the impacts of service changes to certain vulnerable populations, requiring that there not be a disparate impact of changes on these populations. It is possible that focusing transit resources only on productive core routes could negatively impact those riders that need the service most. If a region is arranged in a way that impoverished, minority, or otherwise disadvantaged populations are concentrated in areas that are not well served by the newly improved high frequency core routes, these people will be left behind. This notion of social equity should also be considered by transit service planners.

Making transit service decisions solely based upon their impacts on a single performance measure is an inherently flawed process. While it is essential that transit managers have an informed understanding of the levers at their disposal for increasing transit ridership, they must also consider other factors when making service planning decisions. If route lengths are to be shortened or entire routes eliminated to increase frequency on high-performing routes, it is essential that transit planners consider how the reduction in coverage might affect riders that have traditionally relied on those routes. Could these riders be cut off from essential services or even employment opportunities? When concentrating transit resources it is imperative that transit managers consider the impacts of the changing system to a diverse population of transit riders with an array of needs and dependence on agency services.

6.2 Limitations and Challenges

The most glaring limitation of this study is the use of aggregate data to explain decisions which are individual in nature. Travel behavior, while often described in aggregate terms, is intrinsically personal. One's choice of destination, mode, or departure time is a function of a litany of factors, many of which cannot be feasibly modeled. The solution to this problem is to simplify the equation to a point where the researcher is capable of explaining as much as is possible with the data available.

The aggregate data to explain individual behavior is known in the research lexicon as "ecological fallacy." However, just as troubling as the potential existence of ecological fallacy is the prescription of an aggregated solution that will apply differently to each transit system. This study does not attempt to examine the geographic distribution of transit routes or the systems' interaction with the transportation network as a whole or any disaggregated components of the built environment. We suggest that increasing ridership is possible by favoring service frequency over route density. In no way can we elucidate which routes should be favored or which might warrant reduction or elimination. The finer grain of service planning is beyond the scope of this study, and this will certainly offer a challenge to transit planners as they determine the best way in which to implement the findings of this report.

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