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Nature and/or nurture? Analyzing the determinants of transit ridership across US urbanized areas

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ABSTRACT

Public subsidy of transit services has increased dramatically in recent years, with little effect on overall ridership. Quite obviously, a clear understanding of the factors influencing transit ridership is central to decisions on investments in and the pricing and deployment of transit services. Yet the literature about the causes of transit use is quite spotty; most previous aggregate analyses of transit ridership have examined just one or a few systems, have not included many of the external, control variables thought to influence transit use, and have not addressed the simultaneous relationship between transit service supply and consumption. This study addresses each of these shortcomings by (1) conducting a cross-sectional analysis of transit use in 265 US urbanized areas, (2) testing dozens of variables measuring regional geography, metropolitan economy, population characteristics, auto/highway system characteristics, and transit system characteristics, and (3) constructing two-stage simultaneous equation regression models to account for simultaneity between transit service supply and consumption. We find that most of the variation in transit ridership among urbanized areas – in both absolute and relative terms – can be explained by factors outside of the control of public transit systems: (1) *regional geography* (specifically, area of urbanization, population, population density, and regional location in the US), (2) *metropolitan economy* (specifically, personal/household income), (3) *population characteristics* (specifically, the percent college students, recent immigrants, and Democratic voters in the population), and (4) *auto/highway system characteristics* (specifically, the percent carless households and non-transit/non-SOV trips, including commuting via carpools, walking, biking, etc.). While these external factors clearly go a long way toward determining the overall level of transit use in an urbanized area, we find that transit policies do make a significant difference. The observed range in both fares and service frequency in our sample could account for at least a doubling (or halving) of transit use in a given urbanized area. Controlling for the fact that public transit use is strongly correlated with urbanized area size, about 26% of the observed variance in per capita transit patronage across US urbanized areas is explained in the models presented here by service frequency and fare levels. The observed influence of these two factors is consistent with both the literature and intuition: frequent service draws passengers, and high fares drive them away.

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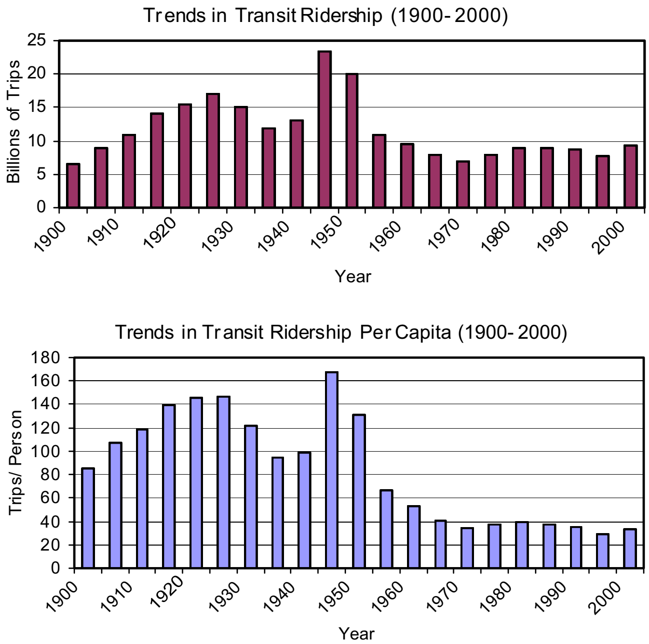

Fig. 1. Trends in transit ridership. *Source:* American Public Transportation Association (2001).

1. Introduction

What explains transit ridership? Why does public transit carry a relatively large share of metropolitan trips in New York City, but such a small share in places like Houston, Atlanta, and Indianapolis? The answers to these questions are both obvious and elusive.

Public transit systems carry large shares of person travel in older, larger metropolitan areas around the globe, but in most places – old and new, large and small – transit is losing market share to private vehicles. Fig. 1 shows that both annual transit ridership and annual ridership per capita in the US peaked during the 1940s. But, with the exception of the fuel, tire, and steel rationing years during and immediately following the Second World War, per capita transit use began to decline significantly during the 1930s and, despite four decades of increasing public subsidy in the US, has remained essentially constant since 1970.

In terms of the market share of metropolitan travel, public transit has for decades been losing customers to private vehicles in the US. Nationally, only 2.1% of all trips were on public transit in 2001, compared to 85.8% by private vehicles, 9.9% by foot and bicycle, and 2.2% by other means (US Department of Transportation, 2001). But consumption of transit service varies dramatically from place to place. Transit use is highest in the centers of the oldest and largest metropolitan areas, and virtually non-existent in many smaller cities and towns. In the US, New York City is the 800-pound transit gorilla – nearly 4 in 10 (38%) transit trips nationally in 2000 were made in the greater New York City area (American Public Transportation Association, 2001).

Even the most casual observer of cities can offer informed speculation on why, for example, the share of year 2000 commuters using public transit in metropolitan San Francisco (19%) was nearly five times higher than in metropolitan Atlanta (4%) (US Census Bureau, 2001). Population density, levels of private vehicle ownership, topography, freeway network extent, parking availability and cost, transit network extent, service frequency, transit fares, transit system safety and cleanliness, and so on all surely play a role. The relative importance of these various factors, and the interaction between them, however, is far from obvious. Understanding the influence of these factors is central to public policy debates over transportation system investments and the pricing and deployment of transit services. But the research literature on explaining transit ridership is surprisingly uneven – and in some cases poorly conceived – with results that are often ambiguous or contradictory.

The causes of transit use and the methodological limitations of much of the literature on the topic are not simply matters of academic interest. Public subsidy of transit service has increased dramatically in recent years in response to a variety of public policy concerns over worsening traffic congestion, air quality, energy consumption, mobility for those without private vehicle access, and disruptions due to street and highway expansion. Total local, state, and federal transit subsidies in the US were $32.2 billion in 2003, a remarkable inflation-adjusted increase of 51.4% since 1990.[2] Why have these enormous, polit-

[2] Authors' calculations of data published by the American Public Transit Association accessed at http://www.apta.com/research/stats/factbook/index.cfm on 31 October 2005.

ically popular investments apparently had so little effect on overall levels of transit use? Is transit use determined primarily by the nature of metropolitan areas, or can the nurture of public policies make a significant difference?

To address these questions we address some of the shortcomings of previous studies of the determinants of transit patronage. We begin by developing a simple causal model hypothesizing the collective influence of a wide range of factors on transit ridership. Given this model, we briefly review and critique the previous research, emphasizing both the principal supportable findings and identifying many of the methodological problems plaguing this literature. We then briefly describe the national data set we developed for this study from the National Transit Database (NTD) and several other sources. We use these data in a cross-sectional regression analysis of transit ridership in two-stage least squares models. Through this approach, we identify an array of factors thought to significantly influence transit ridership and conclude with a discussion of the implications for policy.

In a nutshell, we find that most of the variation in transit ridership among urbanized areas, in both absolute and relative terms, can be explained by the nature of areas – factors outside of the control of public transit systems: (1) *regional geography* (specifically total population, population density, geographic land area, and regional location), (2) *metropolitan economy* (specifically median household income), (3) *population characteristics* (specifically percent Democratic voters and percent carless households), and (4) *auto/highway system characteristics* (specifically non-transit/non-SOV trips, including commuting via carpools, walking, biking, etc.). While these external factors explain most of the observed variation in transit use from place to place, the pricing and deployment of transit service do make a significant difference. We find that the observed range in both fares and service frequency in our sample could account for at least a doubling (or halving) of transit use in a given urbanized area. Controlling for the fact that public transit use is strongly correlated with urbanized area size, about 26% of the observed variance in per capita transit patronage across US urbanized areas is explained in the models presented here by service frequency and fare levels. Properly applied, therefore, the nurture of public policy can have a significant effect on transit use.

2. What determines the consumption of transit?

Basic consumer economics theory tells us that a person consumes a good when the utility of consuming that good is higher than the disutility of its cost. A basic demand function presents the relationship between the cost (or price) of a good and the level of demand. As long as the cost of consuming a good is lower than an individual's willingness to pay, the good is consumed (Dawson, 1983; Varian, 1990). While the demand for transportation is often viewed as derived from the demand for other goods, services, and activities, the application of basic consumer economics theory still holds (Ben-Akiva and Lerman, 1985; Kanafani, 1983; Train, 1993). Thus, the demand for a transit trip can be viewed as a function of both the utility of the trip and its costs: time (access time, wait time, travel time), money (transit fare), and uncertainty (schedule adherence, safety, etc.).

Estimating transit demand functions is complex, however, because the perceived utility and disutility of transit trips varies significantly from person to person and from trip to trip (even for the same person). First, the utility of a transit trip is to a large extent a function of the utility of the activity from which the demand for a transit trip is derived. While the utility, and hence, demand for a particular good, service, or activity can be ascertained, transit is likely just one of many possible ways to access the desired good, service, or activity. Second, the perceived disutility of transit trip costs varies dramatically. Numerous studies have found that travelers perceive out-of-vehicle time (walking to and from transit stops, transferring, and waiting at transit stops) as more onerous (and therefore more costly) than in-vehicle time (Horowitz et al., 1986; Small, 1992; Small et al., 1999; Wardman, 2001). Therefore, someone who lives and works near transit stops on a particular line will likely perceive lower costs for a peak-hour, peak-direction transit trip than will a person traveling between the same two stops, but who lives and works farther from the stops and/or who is traveling at night or weekends when service is less frequent. Third, while some people do not have practical substitutes for transit trips, most do. Relatively fast, flexible private vehicles dominate metropolitan travel and even walking now far exceeds the number of trips made on public transit in the US. Thus, most travelers find the relative utility of traveling by other modes (particularly private vehicles) to be greater than that of public transit for most trips.

The characteristics of transit service obviously affect the perceived costs of transit travel. Basic economic theory tells us that the actual consumption of goods is determined by the equilibrium point between the demand and supply curves under free market conditions (Dawson, 1983; Varian, 1990). Put simply, in the absence of transit service, no service will be consumed, regardless of demand. On the other hand, increasing the network density, reducing headways, and/or lowering fares all lower the perceived cost of transit travel, and move the demand and supply equilibrium point to increase transit patronage. Further, if buses and trains are packed full and service supply is insufficient to accommodate demand, increased service supply will lead to increased consumption of transit trips by accommodating demand previously suppressed due to inadequate supply.

Thus, we can think of the aggregate consumption of public transit service as a function of the collective characteristics of travelers, the physical and economic characteristics of metropolitan areas, the availability of substitute modes for travel, and the price, quantity, and quality of transit services (Fig. 2).

Empirically, the level of service supply (usually measured in terms of vehicle revenue hours or vehicle revenue miles) is highly correlated with the consumption of transit trips in an area. In our sample, the correlation between transit trips and

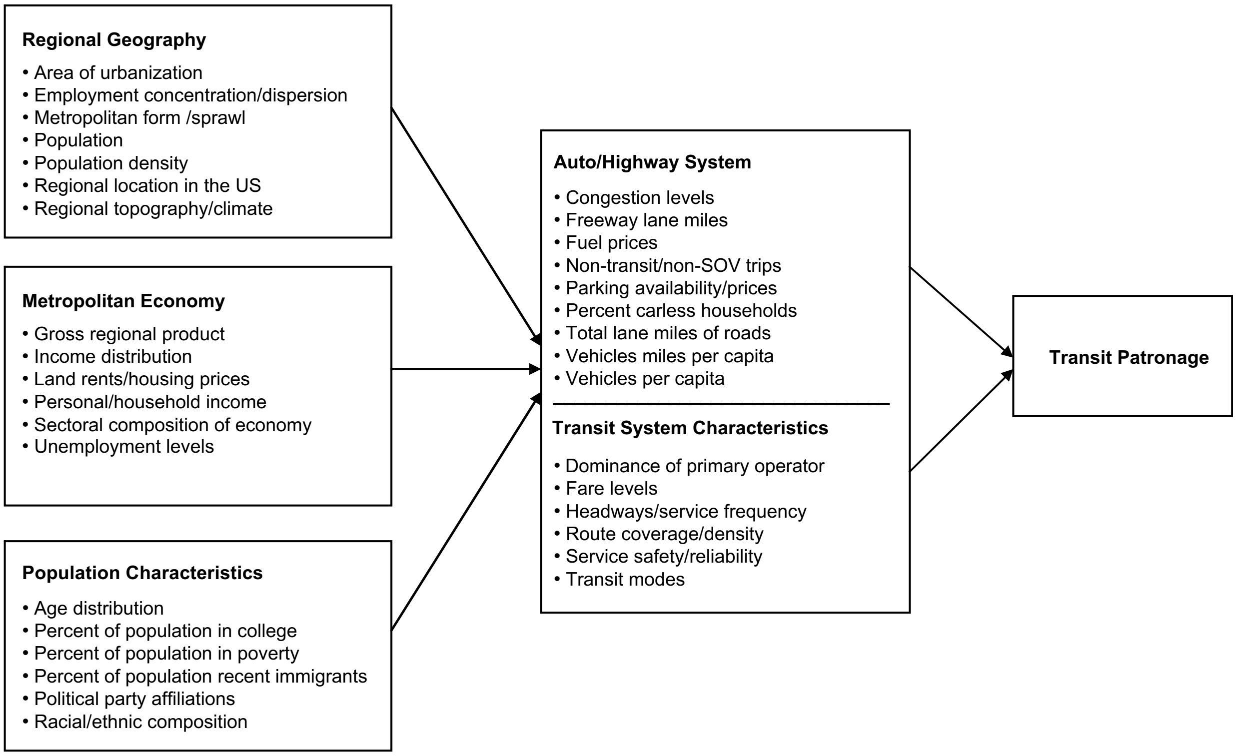

Fig. 2. Conceptual model of the factors influencing aggregate transit demand.

vehicle revenue hours in the US in 2000 was 0.95. While demand and supply functions are independent in microeconomic theory, this is almost certainly not the case for public transit service – a heavily subsidized public service provided to address a wide variety of policy objectives. Obviously, the level of transit consumption, through the actions of government, largely determines the supply of transit service. And just as obviously, the level of transit service supplied in an area significantly influences the consumption of transit trips. Given ongoing efforts to increase public transit patronage around the US, the nature and significance of this circular causality is especially relevant to public policy. For example, if transit consumption is largely a function of factors other than transit supply, increasing transit service may prove a costly and relatively ineffective way to increase transit use. If, on the other hand, transit consumption is strongly influenced by transit service supply, then increasing transit service may be an effective way to promote transit use (Transport and Travel Research Limited & European Commission. Directorate-General Transport, 1996).[3] Thus, when the levels of transit supply and consumption are jointly determined, it is not possible to consider one in isolation from the other. While this public policy conundrum has been addressed at a theoretical level by Berechman (1993) and explicitly in Eqs. (1) and (2) of our conceptual framework below, it has often gone unexamined in studies of the factors explaining transit ridership, to which we now turn.

3. Previous research on the factors affecting transit ridership

Studies of the determinants of transit ridership can be grouped into two general categories: (1) research that focuses on traveler attitudes and perceptions, with both travelers and transit managers as the units of analysis, and (2) studies that examine the environmental, system, and behavioral characteristics associated with transit ridership. In general, the studies of attitudes and perceptions are descriptive in character, while system-focused studies tend to be structured as causal analyses. Both the descriptive and causal analyses examine a host of factors thought to affect transit ridership. These elements can be broadly divided into two categories: (1) external, or control, factors (nature), and (2) internal, or policy, factors (nurture). External factors are largely exogenous to the system and its managers, and include things like service area population and employment. Internal factors are those over which transit managers exercise some control, such as fares and service levels.

[3] Transit service supply is not homogeneous, but instead is defined by a wide array of attributes. While there is a literature on the influence of various transit service features (service frequency, fares, vehicle comfort, service information, and vehicle liveries) on transit use (Cervero, 1990; Horowitz and Thompson, 1995; Martinez, 2003; Dziekan and Kottenhoff, 2006) such data are not collected in a way that would allow their inclusion in the kind of cross-sectional analysis employed here.

The descriptive analyses generally use survey and interview data from transit system managers and transit patrons to assess perceptions of the factors affecting ridership (Abdel-Aty and Jovanis, 1995; Bianco et al., 1998; Brown et al., 2001; Dueker et al., 1998; Jenks, 1995, 1998; Sale, 1976). Perhaps not surprisingly, most of the studies of operator perceptions and views emphasize internal factors. In general, transit managers report five general categories of strategies, programs, and initiatives affecting transit ridership: service improvements and adjustments; fare innovation and changes; marketing and information; new planning approaches and partnerships; and service quality and coordination.

Causal analyses are an attempt to posit and test hypotheses about the factors influencing transit ridership (Cervero, 1990; Chung, 1997; Gomez-Ibanez, 1996; Hartgen and Kinnamon, 1999; Hendrickson, 1986; Kain and Liu, 1995, 1996; Kitamura, 1989; Kohn, 2000; Liu, 1993; McLeod et al., 1991; Morral and Bloger, 1996; Nelson/Nygaard Consulting Associates, 1995; Spillar and Rutherford, 1988; Syed and Khan, 2000). While this is clearly an important area of inquiry for transportation policy research, studies of this type share surprisingly little in terms of data, methods, or findings. Many, but not all, of these studies use multivariate regression analysis to identify the factors most strongly related to changes in transit ridership. One unfortunate commonality between many of the previous studies – small sample sizes – raises questions about both the generalizability and statistical significance of findings (Chung, 1997; Gomez-Ibanez, 1996; Kain and Liu, 1995; Liu, 1993; McLeod et al., 1991; Nelson/Nygaard Consulting Associates, 1995; Spillar and Rutherford, 1988; De Witte et al., 2006). Furthermore, the broad conceptual factors hypothesized to influence ridership and the variables operationalized in these models vary widely (Holmgren, 2007). These problems notwithstanding, these models tend to find that a combination of internal and external variables explains transit ridership. Of the two, external factors (e.g., income, parking policies, development, employment, fuel prices, car ownership, and density levels) are found to have greater effects on ridership than internal factors. Of the internal factors, service quality is often, though not always, found to be more important than low fares.

Descriptive and causal analyses each have advantages and disadvantages. Descriptive analyses are based on sets of often interesting and rich qualitative data from surveys of and interviews with transit operator staff. Thus, these studies focus on what transit managers believe affect transit ridership. Such perceptional data, however, pose methodological and interpretive concerns. This information is subjective and dependent on respondents' perceptions and assumptions about internal and external factors related to ridership (Dueker et al., 1998; Jenks, 1995, 1998). The data are thus subject to bias based on limited or incorrect information. Some of these descriptive studies fail to outline the specific data collection processes used to obtain information (Bianco et al., 1998). In addition, the causal linkages between perceived factors and actual ridership are often simply asserted. Many of these studies are relatively old, and most of them do not specifically ask about perceptions of causality or the relative influence of internal and external factors. Some focus largely, and a few exclusively, on systems that added riders, identifying commonalities among such agencies, but without determining whether such commonalities were shared with or distinct from transit agencies that lost riders (Sale, 1976; Taylor et al., 2002).

Causal analyses have the advantage of being more sophisticated empirical studies – of one, a few, or many agencies – that allow researchers to employ more objective and a wider array of data than those found in descriptive studies. The generalizability of studies looking at a small number of systems is limited, but there is more opportunity for the conceptual development of models. In a few studies, the analysis of data from a large number of agencies produces more robust and generalizable results. However, these studies have their own limitations. Most use readily available data, particularly from the US Census to measure external variables (see, for example, Spillar and Rutherford, 1988). And nearly all examine unlinked, rather than linked, trips (Chung, 1997; Gomez-Ibanez, 1996; Hendrickson, 1986; Kain and Liu, 1995, 1996; Kohn, 2000; McLeod et al., 1991; Spillar and Rutherford, 1988). While much more difficult to measure, linked trips provide a more robust measure of transit ridership.[4] Several studies consider only work trips in the models (Hendrickson, 1986; Morral and Bloger, 1996). Finally, data aggregation and colinearity of variables in many of these studies result in contradictory and/or possibly spurious conclusions regarding the effects of important variables.

Moreover, the models developed in these studies are often not fully specified and there is inconsistency in the variables included. For example, the studies vary widely in the modes examined; some focus specifically on rail or bus (Chung, 1997; Kain and Liu, 1995, 1996), others consider multimodal systems (Gomez-Ibanez, 1996; Hendrickson, 1986), and some attempt to compare findings using both single mode and multimodal data sources (Bresson et al., 2003).

Auto access and operating costs measures are clearly important to transit use, but difficult to operationalize at the level of the transit system or metropolitan area. Additionally, measures of transit service quality, such as driver friendliness, schedule reliability, comfort, and convenience are important, but are difficult, if not impossible, to quantify, especially in the aggregate level.

[4] Most transit patronage data are reported as unlinked trips. A linked trip is one made from an origin to a destination, regardless of the number of transfers involved. For example, a long bus ride to work and a trip of equal time and distance involving two transfers would each count as one linked trip. But while the former is also considered to be one unlinked trip, the latter would count as three unlinked trips. Thus, reconfiguring transit service to increase the number of transfers – which travel behavior studies have consistently found are perceived as burdensome by travelers (Algers et al., 1975; Central Transportation Planning Staff (CTPS), 1997; Guo and Wilson, 2004; Han, 1987; Hunt, 1990; Liu et al., 1997; Wardman et al., 2001) – would likely decrease the number of passengers making linked trips, but could significantly increase the number of unlinked trips reported to funding agencies and public officials. However, as the available cross-sectional data report unlinked rather than linked trips, we have little choice but to analyze unlinked trips consistent with virtually all previous studies of this general topic.

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Most studies employing multiple regression analysis do not take into account the simultaneity between transit supply and consumption (Chung, 1997; Gomez-Ibanez, 1996; Hartgen and Kinnamon, 1999; Kain and Liu, 1995, 1996; Kohn, 2000; Liu, 1993; McLeod et al., 1991). As noted above, this is a serious omission because the causality arrow between transit service supply and consumption points in both directions; in practice, transit operators typically respond to observed changes in service consumption by adjusting service supply, which in turn further influences transit use.

Some previous studies have tried to account for the simultaneity of transit supply and demand (Alperovich et al., 1977; Gaudry, 1975; Kemp, 1981a,b,c; Liu, 1993; Peng et al., 1997). Gaudry (1975) uses a recursive model in which only the ridership level of the previous year, not the current year, affects the level of supply. Peng et al. (1997) use three-stage least squares estimation models to solve both demand and supply equations separately. Alperovich et al. (1977) and Kemp (1981c) use structural equation models to relate variables of demand, supply, and service quality. Kyte et al. (1988) use simultaneous equation transfer function (STF) models to conduct a time-series analysis. Interestingly, Liu (1993) compares coefficients from structural equation ridership models with those obtained in single equation models and concludes that the simultaneous effect between transit demand and supply is likely small. Most of these studies consider the simultaneity of transit demand and supply to develop time-series analyses for particular agencies, with the goal of developing projections of future transit demand in order to modify service levels and routes (Alperovich et al., 1977; Gaudry, 1975; Kemp, 1981a,b; Peng et al., 1997). While such time-series analyses of individual transit operators are certainly relevant to service planning, the findings of these studies may not generalizable to other areas or systems.

Thus, most previous aggregate analyses of the factors influencing transit ridership have examined one or just a few systems, and/or have not included many of the external, control variables thought to influence transit use, and/or have not addressed the simultaneous relationship between transit service supply and consumption. This research attempts to address each of these shortcomings by (1) conducting a cross-sectional analysis of transit use in 265 urbanized areas, (2) testing a wide array of variables measuring regional geography, metropolitan economy, population characteristics, auto/highway system characteristics, and transit system characteristics, and (3) constructing two-stage regression models to account for simultaneity between transit service supply and consumption. How we address each of these issues is detailed in the following section.

4. Accounting for the simultaneity of service supply and consumption in modeling the determinants of transit use

The simultaneity of transit service supply and consumption can lead to biased and inconsistent estimates of coefficients in ordinary least squares (OLS) models. Following Berechman (1993), we can write the demand and supply functions as follows:

The general form of the demand function can be written as

$$D = f(P, T, Y, Q, I, V, Z, R) \tag{1}$$

The general form of the supply function can be written as

$$Y = f(D, E) \tag{2}$$

where D is the transit demand function for the service area; P is the transit fare; T is the vector of travel times; Y is the vector of outputs (service supply); Q is the vector of service attributes; I is the vector of passenger characteristics; V is the vector of prices of alternative modes; Z is the vector of urban characteristics; R is the vector of regional characteristics; E is the vector of other exogenous factors to determine service supply.

If we assume that each vector has only one variable, then Y has only one variable measured in terms of vehicle hours such as Y_{VHi}, and there are no other endogenous variables. Therefore, a simultaneous equation model is expressed by the following:

$$D_i = b_0 + b_1 * Y_{\mathrm{VHi}} + b_2 * P_i + b_3 * T_i + b_4 * Q_i + b_5 * I_i + b_6 * V_i + b_7 * Z_i + b_8 * R_i + u_i \tag{3}$$

$$Y_{\mathrm{VHi}} = c_0 + c_1 + D_i + c_2 + E_i + v_i \tag{4}$$

where i is the individual system or a route.

When D_i is regressed on Y_{VHi} and the other variables in Eq. (3), without taking into account the endogeneity of the two variables, the estimated coefficient for Y_{VHi} will be biased and inconsistent. In order to understand this problem more intuitively, Eqs. (3) and (4) can be simplified as follows:

$$D_i = b_0 + b_1 * Y_{\mathrm{VHi}} + u_i \tag{5}$$

$$Y_{\mathrm{VHi}} = c_0 + c_1 * D_i + c_2 * E_i + v_i \tag{6}$$

Eq. (5) can then be substituted into (6) to get:

$$Y_{\mathrm{VHi}} = c_0 + c_1 * (b_0 + b_1 * Y_{\mathrm{VHi}} + u_i) + c_2 * E_i + v_i \tag{7}$$

$$Y_{\mathrm{VHi}} = \{1/(1 - b_1 c_1)\}\{c_0 + c_1 * b_0 + c_2 * E_i + c_1 * u_i + v_i\} \tag{8}$$

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Therefore,

$$\mathrm{Cov}(Y_{\mathrm{VHi}}, u_i) = E(Y_{\mathrm{VHi}} u_i) \neq 0 \tag{9}$$

Eq. (9) shows that combining independent transit supply and demand variables in a single equation violates one of the conditions of OLS, and thus can lead to biased and inconsistent estimation. For example, assume that u_i increases as Y_{VHi} increases – that is, Y_{VHi} and u_i (or D_i and u_i) are positively correlated. In a single equation model, OLS will produce a slope for the regression model in Eq. (5) that is larger than the actual slope.

One way to address this simultaneity problem is with two-stage least squares (2SLS) regression, which we employ in this study:

Step 1: Regress Y_{VHi} on all exogenous variables for Y_{VHi}, ignoring D_i.
Step 2: Obtain estimated values for Y_{VHi}, $\widehat{Y}_{\mathrm{VHi}}$.
Step 3: Regress D_i on $\widehat{Y}_{\mathrm{VHi}}$ and other exogenous variables for D_i.

5. The data used in this study

The data for this analysis were assembled from a variety of sources. The primary source for the transit-related data was the National Transit Database (NTD), which is compiled annually by the Federal Transit Administration (2004). All transit variables listed in this paper are for the year 2000. The data were compiled individually for each system operator, and then merged for each of the 265 urbanized areas analyzed. Most previous research has used the transit operator as the unit of analysis, but this can be problematic. First, people live, work, and travel in urbanized areas, not in transit operator service areas. Much of the metropolitan data included in our analysis – such as population and employment levels – characterize, and should properly be analyzed at, the urbanized area level. Second, most larger urbanized areas are served by several (and in a few cases dozens of) transit operators with overlapping service area boundaries. Since we hypothesize that transit ridership on any single transit system is explained in part by the total level of transit service provided by *all* operators in an area, it makes sense to analyze transit ridership at the urbanized area level. And third, because federal subsidy formulae allocate funds to transit systems by urbanized area, subsidy levels (particularly for transit capital) are likely to vary systematically by urbanized area. Thus, in contrast to most previous research analyzing one or just a few systems, we chose instead to model transit ridership for each of 265 urbanized areas (UZAs) in the US.

Most of the demographic and other external variables were compiled from the 2000 US Census, Summary File 3 (SF3), and aggregated for each UZA. Examples of these variables include median rent, median household income, total population, and total land area. The bulk of the variables in the models either came from the Census or the NTD. A few others were taken from other sources, including gas prices (US Department of Labor, 2004) and measures of sprawl (Burchell et al., 1998).

Some of the variables required construction from other, simpler variables within each data set. For example, our measure of route coverage is calculated by dividing the total annual service miles by the land area of the urbanized area. Variable construction details are summarized in Table 1 below.

As Table 1 shows, we were not able to operationalize variables for all of the factors hypothesized to affect transit patronage in our conceptual model. While we suspect that several of these factors may be important determinants of transit ridership, we were simply unable to construct related variables. For example, we hypothesize that priced and/or limited parking decreases the utility of automobile travel and, thus, increases the relative utility of transit (Shoup, 2005). However, parking supply and price data are not consistently collected across urbanized areas. Assembling the data and constructing variables from many sources proved to be a time-consuming endeavor.

6. Model specification

Our first step was to test a single-stage OLS model, which did not account for the problem of simultaneity discussed above. This model was similar to what Kain and Liu (1996) developed to analyze changes in transit patronage between 1960 and 1990. Like Kain and Liu, we use natural logarithms to transform variables on both sides of the equation. This transformation is necessary due to the skewness in the distributions of several key variables, such as vehicle revenue hours and UZA population. All of the other variables analyzed were then transformed as well to allow easy interpretation of their coefficients.[5]

The initial single-stage model is summarized as

$$D = D^{\wedge} + \varepsilon f(P, Y, Q, I, V, Z, R) + \varepsilon \tag{10}$$

In this and all following models, all terms are as previously described in Eqs. (1) and (2), with the exception of T because travel time data were not available. The stochastic term is denoted as 'ε'. In testing this model, we initially included as many

[5] In addition, the log transformation of these variables allows us to interpret the parameter estimates of our regression models as constant elasticities. While constant elasticities are less ideal than point or arc elasticities, especially elasticities that vary over the range of the variables, they do permit a crude comparison of our results with previous research, particularly fare and service elasticity studies.

Table 1
Conceptual variables and their operationalization

Category variable	Used	Source	Variable construction	Expected relationship
Regional geography				
Area of urbanization	Yes	Census 2000 SF3	Geographic land area	Unknown
Population	Yes	Census 2000 SF3	Total population	+
Population density	Yes	Census 2000 SF3	Population/geographic area	+
Regional location in US	Yes	Regional dummy variable	UZA in the South (1 = South, 0 = Elsewhere)	–
Employment concentration/ dispersion	*No*	*Not collected*		
Metropolitan form/sprawl	*No*	*Transit Cooperative Research Program*	*Metropolitan sprawl index*	
Regional topography/climate	*No*	*Not collected*		
Metropolitan economy				
Personal/household income	Yes	Census 2000 SF3	Median household income	Unknown
Unemployment levels	Yes	Census 2000 SF3	Unemployed/labor market participants	–
Gross regional product	*No*	*Not collected*		
Income distribution	*No*	*Census 2000 SF3*	*Not constructed*	
Land rents/housing prices	*No*	*Census 2000 SF3*	*Median rent*	
Sectoral composition of economy	*No*	*Bureau of Labor Statistics*	*Not constructed*	
Population characteristics				
Percent of population in college	Yes	Census 2000 SF3	Enrolled college students/total population	+
Percent of population in poverty	Yes	Census 2000 SF3	Poverty population/total population	–
Percent of population recent immigrants	Yes	Census 2000 SF3	Immigrant population/total population	+
Political party affiliations	Yes	2000 Almanac of American Politics	Percent of votes cast for Democrat in 2000 presidential election	+
Racial/ethnic composition	Yes	Census 2000 SF3	Given race/ethnic population/total population	Unknown
Age distribution	*No*	*Census 2000 SF3*	*Given age group population/total population*	
Auto/highway system				
Freeway lane miles	Yes	FHWA Highway Statistics 2000	Freeway lane miles	–
Fuel prices	Yes	Bureau of Labor Statistics	Average price per gallon of gas	+
Non-transit/non-SOV trips	Yes	Census 2000 SF3	Non-transit and non-SOV commutes/all commutes	+
Percent carless households	Yes	Census 2000 SF3	Zero vehicle households/total households	+
Total lane miles of roads	Yes	FHWA Highway Statistics 2000	Total lane miles	–
Vehicle miles per capita	Yes	FHWA Highway Statistics 2000	Daily vehicle miles travelled per capita	–
Congestion levels	*No*	*TTI: Urban Mobility Study*	*Not constructed*	
Parking availability/prices	*No*	*Not collected*		
Vehicles per capita	*No*	*Census 2000 SF3*	*Not constructed*	
Transit system characteristics				
Actual transit service levels	Yes/No	NTD 2000	Total revenue vehicle hours	+
Dominance of primary transit operator	Yes	NTD 2000	Vehicle revenue hours of largest operator/total vehicle revenue hours	+
Fare levels	Yes	NTD 2000	Total revenues/total unlinked trips	–
Headways/service frequency	Yes	NTD 2000	Vehicle revenue miles/route miles	+
Predicted transit service levels	Yes	Two- and three-variables models using different regional geography and auto/highway system variables	Constructed by authors	+
Route coverage/density	Yes	NTD 2000	Route miles/land area	+
Service safety/reliability	*No*	*Not collected*		
Transit modes	*No*	*NTD 2000*	*Not constructed*	

Table 2
The problem of interpreting causality in a single-stage regression model of transit ridership

Variable	Adjusted R^2		0.9733
	Parameter estimate	Pr > |t|	Standardized estimate
Intercept	−5.94265	0.0008	0
Vehicle revenue hours	*1.06456*	*<0.0001*	*0.83418*
Total population	0.10496	0.1303	0.06436
Population density	0.10873	0.2254	0.01908
Percent of population in college	0.14714	0.0180	0.03805
Median household income	0.65461	0.0003	0.06730
Percent of population recent immigrant	0.11828	0.0005	0.05266
Percent voting Democrat in 2000 presidential election	0.23700	0.1538	0.01789
Percent of population African-American	−0.01551	0.5195	−0.00961
Freeway lane miles	0.00009	0.9982	0.00006
Average gas price	0.73675	0.0391	0.02745
Percent carless households	0.60709	<0.0001	0.09209
Dominance of primary transit operator	0.29820	0.0518	0.02602
Transit fares	−0.35421	<0.0001	−0.10798
Headways/service frequency	0.04849	0.3687	0.01330

of the key measures identified in Table 2 as possible. We then worked through a process of gradually eliminating (1) highly correlated independent variables and (2) variables not significantly correlated with the outcome measure to eventually arrive at a parsimonious single-stage OLS model.

After confirming that our results were generally consistent with the findings of previous studies, we constructed two-stage models. The first stage uses exogenous variables to estimate the supply of transit; this term is then used as an independent variable in the second stage:

$$Y = \widehat{Y} + \varepsilon_1 = g(E) + \varepsilon_1 \tag{11}$$

$$D = D^{\wedge} + \varepsilon_2 = f(P, \widehat{Y}, Q, I, V, Z, R) + \varepsilon_2 \tag{12}$$

We produced two forms of this general model. The first was based on total supply of and demand for transit service. But because the metropolitan area population proved to be such an overwhelming determinant of absolute transit patronage, we also produced a second set of models estimating the determinants of per capita transit ridership.

We present our model results here in two parts – first for total urbanized area ridership, and then for relative (per capita) ridership. We present below models that test a wide array of external and internal factors hypothesized to influence transit patronage – first without and then with instrumental variables to predict transit service levels.

7. Analyzing total urbanized area transit ridership

Table 2 presents the results of our initial regression of a wide array of external and internal factors hypothesized to influence aggregate transit ridership. As with most other analyses of this sort, the results indicate service levels (measured here as vehicle revenue hours of service) are – by far – more strongly associated with transit ridership than any of the other variables tested (Std Est = 0.83418). The relationship is so strong that it leaves little unexplained variance to be accounted for by the other variables. In fact, a simple one-variable regression finds that, in this sample of 265 urbanized areas, Vehicle revenue hours of service explains 95% (R^2 = 0.9503) of the variation in transit patronage.

Among the other *transit system characteristics* tested, transit fares exhibited the expected negative and significant relationship with ridership. The dominance of a single transit operator in area was also positively and significantly related to patronage, though like all independent variables other than vehicle hours of service, the magnitude of the effect was relatively small. Route density was excluded from this model because it was so highly correlated with population density. However, a simple, two-variable regression model using route network density and service intensity as independent variables explains 55% (R^2 = 0.5529) of the variation in transit ridership. In this model, both service quality variables are positively and significantly related to ridership, with service intensity (Std Est = 0.67575) explaining more variation than route network density (Std Est = 0.42086).

For the *auto/highway system* variables tested, the percent of zero vehicle households was positively and significantly related to transit patronage, as expected. The sign for regional fuel prices was as expected, but the variable was on the margin of significance. This is likely due to the relatively low levels of variation of average fuels prices (less than $0.30 for 95% of the urbanized areas in our sample) between one urbanized area and another.

Both of the *regional geography* variables tested (population density and total population) displayed the expected signs. Both variables were highly correlated with vehicle revenue hours and, thus, neither tested as statistically significant in this model. Among the *metropolitan economy* variables tested, median household income exhibited the expected positive and significant relationships with ridership.

Table 3
First stage – estimating total urbanized area transit service vehicle revenue hours

Variable	Adjusted R^2		0.8216
	Parameter estimate	Pr > $\|t\|$	Standardized estimate
Intercept	−5.44638	<0.0001	0
Total population	1.15134	<0.0001	0.89730
Percent voting Democrat in 2000 presidential election	0.71598	0.0071	0.07121

Among the *population characteristics* we tested, the percent of recent immigrants and percent of college students in the population both exhibited the expected signs and were statistically significant. The insignificance of the poverty variable is likely due to the fact that the highest apparent poverty rates among urbanized areas are in college towns (full of temporarily poor students), like Gainesville, Florida, and Iowa City, Iowa, which have relatively high levels of transit ridership, and in smaller, agriculturally-based cities, like Brownsville, Texas, and Bakersfield, California, which tend to have relatively low levels of transit ridership.

The observed relationship between the percent African-American and transit patronage is negative, which is not consistent with an extensive literature on race/ethnicity and transit use (Doyle and Taylor, 2000; Giuliano, 2003; Johnston-Anumonwo, 1995; McLafferty and Preston, 1997; Pisarski, 1996; Rosenbloom, 1998; Taylor and Ong, 1995). In general, studies of African-American households (rather than the African-American population in urbanized areas analyzed here) find that transit use among blacks tends to be higher compared to other those in other racial/ethnic groups, even after controlling for age, income, and other social and demographic factors through to influence transit use.

While our counter-intuitive result may be explained in part by the high level of colinearity between percent African-American and percent of poverty households in the sample, it is more likely the result of regional geography: southern cities tend to have both high proportions of African-Americans and relatively low levels of transit service. In other words, as discussed in more detail below, while African-American households tend to patronize public transit more frequently than households from other racial/ethnic groups, they are also more likely to reside in urbanized areas with lower than average levels of transit service.

As discussed in the review of the literature, the obvious simultaneity between transit service supply (measured here as vehicle revenue hours) and transit service demand (measured as passenger boardings) makes interpreting the results of this initial model problematic. To address this issue, we use a simultaneous equations approach to first develop a model to predict transit service supply, and then to use the predicted service supply variable from this first model as an instrumental variable in a second model to predict transit service demand.

Table 3 presents the results of the first-stage model estimating total urbanized area vehicle hours of transit service. We tested a variety of models to predict total vehicle revenue hours, and settled on a simple two-variable model for the first stage using urbanized area population and the percent of the population voting in each UZA for the Democrat in the 2000 presidential election, which explains over 80% (R^2 = 0.8216) of the variation in vehicle hours of service. The logic here is that large metropolitan areas are likely to have proportionately more transit service, while Democratic-leaning areas are more likely to support public expenditures on transit subsidies.

Table 4
Urbanized areas with the greatest deviations from predicted values

	Name	Unlinked trips	Vehicle revenue hours	Total population
Undersupply	Kingsport, TN-VA Urbanized Area	53,872	5957	95,766
	Montgomery, AL Urbanized Area	21,363	9657	196,892
	Lewiston-Auburn, ME Urbanized Area	123,492	11,295	50,567
	Key West, FL Urbanized Area	350,222	14,734	35,866
	Greenville, SC Urbanized Area	578,508	33,015	302,194
	Port Arthur, TX Urbanized Area	160,776	14,616	114,656
	St. Joseph, MO-KS Urbanized Area	171,298	23,539	77,231
	Hagerstown, MD-WV-PA Urbanized Area	290,725	28,036	120,326
	Phoenix-Mesa, AZ Urbanized Area	35,812,539	1,057,971	2,907,049
	Benton Harbor-St. Joseph, MI Urbanized Area	27,805	3899	61,745
Oversupply	Olympia-Lacey, WA Urbanized Area	2,782,800	126,744	143,826
	Bremerton, WA Urbanized Area	3,538,482	119,046	178,369
	Bellingham, WA Urbanized Area	2,918,916	86,818	84,324
	Seaside-Monterey-Marina, CA Urbanized Area	4,016,332	189,351	125,503
	Johnstown, PA Urbanized Area	1,534,473	63,654	76,113
	Ithaca, NY Urbanized Area	2,571,605	115,688	53,528
	Athens-Clarke County, GA Urbanized Area	1,363,068	39,472	106,482
	Florence, SC Urbanized Area	179,295	35,369	67,314
	Rome, GA Urbanized Area	966,960	24,990	58,287
	Iowa Falls, IA Urban Cluster	1,256,482	45,716	4908

Table 5
Urbanized areas with the highest and lowest proportions of African-Americans

Rank	Urbanized area	Population	% African-American	Region
1	Albany, GA	95,611	56.6	South
2	Jackson, MS	293,192	50.7	South
3	Montgomery, AL	197,017	49.9	South
4	Memphis, TN-MS-AR	971,282	46.4	South
5	Savannah, GA	208,885	44.0	South
6	New Orleans, LA	1,009,015	43.2	South
7	Danville, VA	50,608	42.6	South
8	Shreveport, LA	275,094	42.3	South
9	Alexandria, LA	78,525	41.9	South
10	Monroe, LA	113,947	40.9	South
256	Bellingham, WA	84,499	0.7	Pacific NW
257	Pocatello, ID	62,514	0.7	Pacific NW
258	Boise City, ID	272,656	0.6	Pacific NW
259	Medford, OR	128,797	0.5	Pacific NW
260	Redding, CA	105,258	0.5	Pacific NW
261	Billings, MT	100,051	0.4	Pacific NW
262	Laredo, TX	175,841	0.4	South
263	Logan, UT	76,141	0.4	Pacific NW
264	Wausau, WI	68,281	0.3	Midwest
265	Missoula, MT	69,502	0.2	Pacific NW

The predicted vehicle revenue hours variable from the first-stage model was then used as an instrumental variable in a second model to predict transit patronage. Creating a predicted service hours variable allows us to identify urbanized areas that provide more or less transit service than would otherwise be expected based on the size and political culture of the area. Some areas, like Honolulu, Hawaii, and Ithaca, New York, provide substantially more transit service than would be predicted, while others, like Montgomery, Alabama, and Nashua, New Hampshire, provide substantially less transit service. Thus, this difference between the predicted and actual levels of transit service can be interpreted as one indicator of the policy effects on transit service supply. Table 4 lists the 10 urbanized areas where actual transit service levels most exceed predicted levels (apparent oversupply), and the 10 urbanized areas where actual transit service levels are furthest below predicted levels (apparent undersupply).

In examining the urbanized areas that diverge most dramatically from the expected levels of transit supply, several things jump out. Among urbanized areas with more transit than would be expected, several are dominated by large universities, which frequently have substantial transit systems designed to serve the university community. Others, like San Francisco, have urban densities conducive to transit and have limited parking. With the exceptions of Phoenix, Arizona and Lewiston-Auburn, Maine, the cities with less transit than predicted tend to be relatively small metropolitan areas disproportionately located in the South.[6]

While Southern urbanized areas tend to supply less transit service than in other parts of the US, they also tend to be more politically conservative,[7] poorer, and, as noted above, have higher proportions of African-Americans. Fifty-four of the 69 UZAs (78.3%) where African-Americans comprise more than 16% of the population are in the South, while just three of the 68 UZAs (4.4%) where African-Americans comprise less than 4% of the population are in the South (Table 5).

Table 6 presents the results of a second stage model predicting transit ridership. Among the *transit system characteristics* variables in the second of this two-stage model, the predicted vehicle revenue hours variable, not surprisingly, explains most (Std Est = 0.74293) of the variation in transit ridership, but, as hypothesized, less than the actual service hours variable tested in Table 2 above.

In addition to the effects of metropolitan area population size and political orientation in predicting absolute transit service levels, we again included the same set of variables representing *transit system characteristics*, *auto/highway system*, *regional geography*, *metropolitan economy*, and *population characteristics* tested above, with the addition of a regional dummy variable (1 = South, 0 = Elsewhere). The most significant of these explanatory variables are the percentage of zero vehicle households (+), transit service frequency (+), and average fare (−). Most of the explanatory variables in this model behave as predicted, with the exception of percent African-Americans in the population (–), which again ran counter to what would be expected based on the literature. However, given the high level of colinearity between many of the independent variables tested, we tested several models in developing a more parsimonious two-stage regression model to predict overall transit ridership in an urbanized area.

Table 7 shows this more parsimonious model, which includes variables for six (external) factors outside of the control of transit systems: (1) the ambient level of transit service demand (measured by the predicted level of vehicle revenue hours

[6] A historically, culturally, and politically distinct region of the United States, the South is defined by the US Census Bureau as comprising 17 jurisdictions: Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, Washington, DC, and West Virginia.

[7] In 2004, the South was comprised of 14 "red" states (i.e., all of their Electoral College votes for President went to the Republican candidate, George W. Bush) and just two "blue" states, Delaware and Maryland (where the Electoral College votes went to the Democratic candidate, John Kerry).

Table 6
Second stage – test the influence of a wide array of variables on total urbanized area transit ridership

Variable	Adjusted R^2		0.9105
	Parameter estimate	Pr > |t|	Standardized estimate
Intercept	−3.22843	0.0412	0
Predicted vehicle revenue hours	1.03798	<0.0001	0.74293
Population density	0.48687	0.0030	0.08545
Unemployment rate	−0.22606	0.1975	−0.03159
Percent of population in college	0.24687	0.0108	0.06384
Percent of population recent immigrants	0.15396	0.0137	0.06854
Percent of population African-American	−0.06940	0.1310	−0.04302
Freeway lane miles	0.01571	0.8153	0.01025
Average gas price	1.45192	0.0288	0.05410
Percent carless household	1.17548	<0.0001	0.17831
Transit fares	−0.45460	<0.0001	−0.13858
Headways/service frequency	0.51214	<0.0001	0.14048

Table 7
Second stage – final estimation of the factors influencing total urbanized area transit ridership

Variable	Adjusted R^2		0.9125
	Parameter estimate	Pr > |t|	Standardized estimate
Intercept	−1.85237	0.1899	0
Predicted vehicle revenue hours	1.08126	<0.0001	0.77391
Population density	0.42365	0.0086	0.07435
UZA in the South	−0.12621	0.0014	−0.07823
Percent of population in college	0.22837	0.0182	0.05905
Percent of population recent immigrants	0.19278	0.0015	0.08582
Percent carless households	1.19041	<0.0001	0.18057
Transit fares	−0.42660	<0.0001	−0.13004
Headways/service frequency	0.50284	<0.0001	0.13793

estimated in the first model), (2) the density of the urbanized area (measured in terms of population density), (3) whether the UZA is located in the South, (4) the proportion of college students in the population, (5) the proportion of immigrants in the population, and (6) the proportion of the population with little or no access to private vehicles (measured by the percent of zero vehicle households). The model also includes two (internal) factors over which transit systems exercise control: (1) service frequency (measured as vehicle revenue miles of service divided by route miles) and (2) the transit fare (measured as total fare revenues divided by total unlinked trips). In this model, predicted service supply (Std Est = +0.77391) has, by far, the strongest relationship with transit patronage, followed by the percent carless households (Std Est = +0.18057) and the two policy variables: transit service supply (Std Est = +0.13793) and transit fares (Std Est = −0.13004).

8. Analyzing per capita urbanized area transit ridership

The enormous influence that urbanized area population has on transit service supply and, in turn, levels of transit patronage can act to obscure the other factors – both external and internal to transit systems – that combine to explain riance in transit use from place to place. Accordingly, we conducted a second analysis of the factors influencing per capita levels of transit ridership to control for the influence of urbanized area population size on ridership.

Reliably predicting vehicle revenue hours per capita, however, proved far more challenging than predicting overall levels of transit service (Table 8). Our final first-stage model estimating vehicle revenue hours per capita comprised three independent variables: population density, proportion of zero vehicle households, and whether the urbanized area is located in the South. As expected, population density and the proportion of zero vehicle households is positively associated with increased per capita levels of transit service, while Southern urbanized areas, as discussed above, tend to supply less transit service than in other parts of the US. Collectively, these three variables explained 29% ($R^2 = 0.2921$) of the variation in vehicles service hours per capita, substantially less than the 82% explained in the first stage of the total ridership models.

Our initial second stage model estimating per capita transit ridership (not shown) included the predicted per capita transit service variable from the first-stage model and nine other independent variables representing *regional geography*, *metropolitan economy*, *population characteristics*, the *auto/highway system characteristics*, and the *transit system characteristics*. However, the explanatory power of this model ($R^2 = 0.7079$) was slightly lower than of a more parsimonious model with four fewer independent variables ($R^2 = 0.7111$) (Table 9).

In this parsimonious per capita model, predicted service levels again explain most of the observed variance in ridership (Std Est = +0.45166). Interestingly, the three remaining (external) explanatory variables for *regional geography* (geographic

Table 8
First stage – estimating urbanized area transit service vehicle revenue hours per capita

Variable	Adjusted R^2		0.2921
	Parameter estimate	Pr > |*t*|	Standardized estimate
Intercept	−4.99749	<0.0001	0
Population density	0.76335	<0.0001	0.37337
UZA in the South	−0.19278	0.0168	−0.13223
Percent carless households	0.66520	<0.0001	0.28856

Table 9
Second stage – final estimation of the factors influencing urbanized area transit ridership per capita

Variable	Adjusted R^2		0.7111
	Parameter estimate	Pr > |*t*|	Standardized estimate
Intercept	−9.38827	0.0003	0
Predicted vehicle revenue hours	1.23006	<0.0001	0.45166
Geographic land area	0.19365	<0.0001	0.20245
Median household income	0.92123	0.0009	0.17614
Non-transit/non-SOV trips	1.12844	<0.0001	0.24220
Transit fares	−0.51532	<0.0001	−0.29327
Headways/service frequency	0.48399	<0.0001	0.24600

Table 10
Testing the sensitivity of policy variables in predicting total UZA and per capita transit ridership

	R^2 (%)
Total ridership models	
Environmental variables only	85.7
Environmental + policy variables	90.9
Percent change in adjusted R^2	6.1
Per capita ridership models	
Environmental variables only	44.6
Environmental + policy variables	70.4
Percent change in adjusted R^2	57.7

land area, Std Est = +0.20245), *metropolitan economy* (median household income, Std Est = +0.17614), and *auto/highway system* (commuting by means other than public transit or driving alone, Std Est = +0.24220), and the two (internal) *transit system* variables (transit fares, Std Est = −0.29327 and service frequency, Std Est = +0.24600)[8] all appear to have roughly similar levels of influence on per capita ridership. To sum, larger, wealthier urbanized areas that host high levels of carpooling, walking, and biking to work tend to have higher levels of transit use per capita. In such areas, frequent transit service and relatively low transit fares combine to increase transit trips per person as well.

9. The relative roles of internal and external factors in determining transit use

What are the relative roles of environmental (external) and policy (internal) factors in determining transit use? In other words, how much influence do transit system managers have in nurturing patronage in their service areas, and how much is due to the "natural" endowments of the area?

Collectively, the six external and two internal variables in the final total urbanized area ridership model (Table 7) explained 91% (R^2 = 0.9125) of the variation in overall transit boardings in our sample. The six external control variables in this model appear to account for most of the observed variation in ridership, though the two internal, policy variables have small, albeit non-trivial effects on ridership. To test the relative influence of the two internal variables in predicting overall ridership, we re-ran this model omitting the service and fare variables. The resulting model explained about 86% (R^2 = 0.8574) of the variation in overall urbanized area transit boardings (Table 10).

Similarly, we re-ran the per capita ridership model excluding these two variables to test the relative influence of the two (internal) transit system variables for service frequency and fares. In contrast to the models of total urbanized area ridership that were explained largely by total population, removing the two transit policy variables from the per capita ridership

[8] This per capita model estimates a fare elasticity of −0.51, which is somewhat higher than the short-run fare elasticities of −0.3 (rail) and −0.4 (bus) estimated by Balcombe (2004), and slightly lower than the medium run elasticities of −0.6 (rail) and −0.56 (bus) estimated in the same review.

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Table 11
Testing the sensitivity of policy variables in predicting UZA transit ridership (assuming average values for all control variables)

	5th percentile	95th percentile	% difference
Average fare per unlinked boarding	$0.95	$0.20	−78.9
Predicted total UZA boardings	1,997,654	3,877,349	94.1
Predicted per capita UZA boardings	7.1	15.6	119.7
Annual service miles per route mile	2340	12,803	447.2
Predicted total UZA boardings	1,706,643	4,011,662	135.1
Predicted per capita UZA boardings	6.4	15.1	135.9

model caused the adjusted R^2 to drop by 37% from 0.7035 to 0.4461. This suggests that, controlling for urbanized area population, over one-quarter (25.8%) of the observed variance in per capita transit ridership among the 265 urbanized areas examined here can be explained by transit service frequency and fare levels (Table 10).

A second way to test the relative influence of environmental (external) variables and policy (internal) variables on transit ridership is to separately test the effects of fares and headways on patronage in our models. Here we multiply each of the external variable coefficients and one of the two internal variable coefficients estimated in the final total (Table 7) and per capita (Table 9) ridership models by the average value observed for each of these variables in the sample. We then multiply the other policy (internal) variable first by the observed 5th percentile value and then the 95th percentile value observed in the sample. This allows us to estimate the relative influence of changes in the average fare per unlinked trip and service frequency using values actually observed in our sample of 265 urbanized areas.

Table 11 presents the results of this analysis and shows that both average fare levels[9] and average levels of service frequency vary by more than a factor of four from urbanized area to urbanized area in the US. This level of fare variance, in the average case, is estimated to double (or halve) both total and per capita urbanized area ridership. Likewise, the observed level of variance in service frequency *ceteris paribus*, would be estimated to more than double (or more than halve) total urbanized area transit patronage.

A 2004 TRL Limited report summarized the findings from a wide variety of studies of the factors related to the demand for public transit, primarily in the UK and Europe (Balcombe, 2004). In terms of fare elasticities, this research review distinguished between short-run (1–2 years), medium-run (5–7 years), and long-run (12–15 years) elasticities, as well as modal differences (bus, metro, and local suburban rail). While our cross-sectional models that aggregate all transit service data for a given urbanized area do not take into account such time and modal factors, we can broadly compare our parameter estimates (which, as log-log models, can be interpreted as constant elasticities) to these findings summarized in Balcombe's (2004) review.

Balcombe (2004) notes that aggregate studies in the 1980s led to the generally accepted fare elasticity for public transit of −0.3 for what would generally be considered a short-run fare elasticity. However, more recent studies suggest that the fare elasticity is closer to −0.4,[10] almost identical to the estimated fare elasticity of −0.43 in our final total ridership model (Table 7). The estimated fare elasticity of −0.51 estimated in our final per capita ridership models (Table 9) is somewhat above Balcombe's estimated short-run fare elasticity of −0.4, but just below his estimated medium-run elasticities of −0.6 (rail) and −0.56 (bus) (Balcombe, 2004).

Likewise, Balcombe summarizes the findings from a wide variety of service elasticity studies. Elasticities with respect to vehicle hours and to service frequency are relevant to this discussion, as they remained in our final models. Our estimated service elasticities with respect to vehicle hours are 1.1 (Table 7) and 1.2 (Table 9), which are comparable to the 1.14 and 1.03, respectively, Balcombe cites as service elasticities reflecting the compound effects of increases in service hours and frequency of services from the studies in Santa Clarita and Santa Monica, California (Balcombe, 2004, p. 76).[11] Our estimated elasticities with respect to service frequency can be approximately compared to headway elasticities in other studies. While our urbanized area analyses aggregate all transit modes in a given area, our estimated service elasticities with respect to service frequency across urbanized areas are 0.50 in our overall ridership models (Table 7) and 0.48 in our per capita ridership models (Table 9). Service elasticities are comparable between frequency and headway measures when the observed change is 10% or less, as a 10% increase in frequency translates into a 9% reduction in headways. Given this, our estimated service elasticities are

[9] The average fare per unlinked boarding is typically well below the base fare on any transit system for several reasons. First, many patrons – such as students and the elderly – typically pay substantially discounted fares. Second, unlimited ride pass users (such as monthly passes) are often purchased by very frequent riders who can end up paying a very low average fare per ride. And, third, because transfers on a single fare trip count in the data as two unlinked trips, the average fare per unlinked boarding can be well below the average fare per linked boarding.

[10] Balcombe's review of the research indicates that "broadly speaking: bus fare elasticity averages around −0.4 in the short run, −0.56 in the medium run and −1.0 in the long run; metro fare elasticities average around −0.3 in the short-run and −0.6 in the long run, and local suburban rail around −0.6 in the short-run" (2004, p. 15).

[11] Service level can be measured in vehicle kilometers or vehicle miles. In this case, reported short-run and long-run elasticities for bus service are 0.4 and 0.7, and reported short-run elasticities are 0.75 for rail service (Balcombe, 2004).

nearly identical to the headway elasticities reported by Balcombe, who finds an average value of −0.49 with a range of −0.33 to −0.65 (Balcombe, 2004, 73).

10. Conclusion: implications for policy

Most previous aggregate analyses of the factors influencing transit ridership have examined one or just a few systems, have not included many of the external, control variables thought to influence transit use, and have not addressed the simultaneous relationship between transit service supply and transit patronage demand. This study has attempted to address each of these shortcomings in the previous research by (1) conducting a cross-sectional analysis of transit use in 265 urbanized areas, (2) testing dozens of variables measuring transit system characteristics, auto/highway system characteristics, regional geography, metropolitan economy, and population characteristics, and (3) constructing two-stage simultaneous equation regression models to account for simultaneity between transit supply and demand.

Aggregate analyses like these clearly have limitations. While using urbanized areas, rather than individual transit systems, as our unit of analysis allowed us to consider the collective efforts of multiple transit agencies in urban areas and to include and test a wide array of regional, economic, and demographic variables on aggregate transit ridership, such a relatively coarse unit of analysis does not allow us to meaningfully evaluate a wide array of factors – such as personal safety, schedule reliability, and parking availability and costs – thought to significantly influence transit use. Further, aggregating to the urbanized area allows for between-group comparisons, but ignores the significant within group variation in transit service and use in nearly every record in our sample. This is particularly important for public transit because the transit use varies dramatically across metropolitan areas; in many areas, a substantial share of transit ridership is concentrated on just a few lines in and around the core of central cities, with far lower levels of patronage elsewhere. Such variation is not captured in this analysis.

The enormous variation in the size, character, population, and transit use among the 265 US urbanized areas analyzed provides us with substantial variance in most of the variables tested, which is an advantage of the cross-sectional models employed here. However, our analysis necessarily assumes that the factors influencing transit use operate somewhat consistently across urbanized areas, which may not be the case. For example, we present fare and service elasticities that do not distinguish among modes or between the short- and long-run. The difference between short- and long-run elasticities can be examined using time-series data with lagged specifications.[12]

Even if such data were available, however, given the generally gradual evolution of factors thought to influence transit patronage in urban areas, it is quite possible that time-series data over relatively short periods of time will have not sufficient variance in many of the variables tested in our models. One common problem with lag models is inadequate variance in the variables tests.[13] And, as noted in the literature review above, while time-series data for individual agencies or areas are easier to come by, the results are unlikely to be generalizable. Resources permitting, however, we hope to construct and test multi-year data sets for the urbanized areas examined here in the future.

Further, a common problem with cross-sectional models is underspecification. Underspecification bias in cross-sectional analyses is reduced when a sufficient number of variables thought to explain different aspects of the observed variance in a dependent variable are tested. As such, we tried in this analysis to develop a clear causal model and to test a wide array of variables that we believe influence different aspects of the variance in transit patronage.

Such limitations notwithstanding, we find that most of the variation in transit ridership among urbanized areas – in both absolute and relative terms – can be explained by factors outside of the control of public transit systems: (1) *regional geography* (specifically, area of urbanization, population, population density, and regional location in the US), (2) *metropolitan economy* (specifically, personal/household income), (3) *population characteristics* (specifically, the percent college students, recent immigrants, and Democratic voters in the population), and (4) *auto/highway system characteristics* (specifically, the percent carless households and non-transit/non-SOV trips, including commuting via carpools, walking, biking, etc.) (Table 12).

While the nature of an urbanized area clearly goes a very long way toward explaining the overall level of transit use in an urbanized area, we find that transit policies – measured here in terms of service frequency and fare levels – do make a significant difference as well. Table 11 shows that the observed range in both fares and service frequency in our sample could account for at least a doubling (or halving) of transit use in an urbanized area. Controlling for the fact that public transit use is strongly correlated with urbanized area size, about 26% of the observed variance in per capita transit patronage across US urbanized areas is explained in the models presented here by variations in service frequency and fare levels (Table 10). The observed influence of these two principal components of transit service is consistent with both the literature and intuition: frequent service draws passengers and high fares drive them away.

[12] There is, however, a disadvantage to employing time-series analyses from just one location – as we note in the manuscript. Time-series analyses with lagged variables for a single agency may be a more appropriate way to estimate fare elasticities for a given transit system, but the results may not be applicable to other systems, though they are often presented as broadly generalizable in the literature.

[13] Kenneth Small (2007, personal communication with authors).

Table 12
Summary of model results

	Absolute transit service/ridership			Per capita transit service/ridership		
	First stage: service levels	Second stage: full model	Second stage: parsimonious	First stage: service levels	Second stage: full model	Second stage: parsimonious
Regional geography						
Area of urbanization					+	+
Population	+					
Population density		+	+	+		
Regional location in US (UZA in the South)			–	–		
Metropolitan economy						
Personal/household income					+	+
Unemployment levels		–				
Population characteristics						
Percent of population in college		+	+			
Percent of population in poverty						
Percent of population recent immigrants		+	+		+	
Political party affiliations (percent Democrat)	+					
Racial/ethnic composition (percent African-American)		–				
Auto/highway system						
Fuel prices		+			+	
Freeway lane miles		+				
Non-transit/non-SOV trips					+	+
Percent carless households		+	+	+		
Total lane miles of roads						
Vehicle miles per capita					–	
Transit system characteristics						
Dominance of primary transit operator					+	
Fare levels		–	–		–	–
Headways/service frequency		+	+		+	+
Predicted transit service levels		+	+		+	+
Route coverage/density						

While seemingly obvious, these findings do not necessarily square with trends in US public transit policy over the past two decades, which emphasize capital investments in expensive new rail and busway lines that concentrate both expenditures and service improvements on just one or a few lines, over systemwide improvements in service frequency or innovations in transit pricing (Wachs, 1989; Li and Taylor, 1998; Taylor and Samples, 2002). This perhaps helps to explain why inflation-adjusted subsidies on public transit increased 51.4% between 1990 and 2003, while vehicle miles of service grew by only 23.1%, and passenger boardings just 7.2%, over the same period.[14] So while we have shown in this analysis that the nurture of public policy can significantly affect transit use, policymakers and transit system managers would appear to have much to learn about which policies return the most ridership bang for the subsidy buck.

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[14] The authors' calculations were based on data published by the American Public Transit Association and accessed at http://www.apta.com/research/stats/factbook/index.cfm on 31 October 2005. In a review of 11 international studies of the effects of public subsidy expenditures on transit use, Bly et al. (1980) and Transport and Travel Research Limited & European Commission. Directorate-General Transport (1996) collectively report a range of elasticities between +0.2 and +0.4. However, the causal relationship between subsidy expenditures and transit use is complex. While subsidies can be used to increase service and keep fares low, studies of increasing transit subsidies in the 1970s and 1980s found that a large share of the subsidy growth went to increased labor compensation and associated declines in labor productivity (Lave, 1985; Pickrell, 1988).

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