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Title:

Does service reliability influence transit patronage? Evidence from Los Angeles, and implications for transit policy

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Abstract

This paper explores whether service reliability determines transit patronage. Using a unique historical archive of service supply, performance, and patronage data from the Los Angeles Metro bus and rail system, we analyze whether service reliability explains in part the variation in patronage across transit lines during weekday peak and off-peak periods. By estimating a simple single-stage model of transit line patronage, and a simultaneous equations model to address the recognized endogeneity between transit service supply and consumption, we provide conclusive evidence that service reliability is indeed a significant determinant of peak-period patronage. This means that, all else equal, more reliable transit lines can attract more patrons across their service corridors as they are chosen over alternate lines and competing modes. Our paper presents first empirical evidence on the demand for transit service reliability. Results suggest that transit agencies can expect some system-wide patronage gains from reliability improvements. From a policy perspective, reliability investments may be cost-effective means for increasing productivity of transit lines and systems.

Keywords: Public transportation; Transit service reliability; Public transit policy

1. Introduction

1.1 Research context

The US public transit industry has experienced substantial growth in funding support over the past several decades. For example, between 1992 and 2012, total annual government[1] spending on transit increased steadily from $22 billion to $58 billion at an annual average inflation-adjusted growth rate of about 2.5 percent.[2] The trend continues. Recently, the new surface transportation law, MAP-21[3], authorized more than $20 billion[4] just for federal transit programs over two fiscal years (2013 and 2014). Continued funding commitments from federal, state, and local governments have helped expand transit service areas, improve service quality levels, upgrade fleets, maintain core infrastructures, and sustain operations.

Unfortunately, in spite of ambitious service expansion and modernization programs, transit continues to struggle with rising cost and operational inefficiency. Patronage growth has not kept pace with capital investments and rising O&M[5] costs; and transit's share of the US travel market continues to be marginal.

Figures from the US National Transit Database (NTD) and the National Household Travel Surveys (NHTS)[6] are illustrative. Between 2002 and 2011, national system-wide transit service supply, measured as annual total vehicle revenue miles, increased by 14.2 percent, while unlinked passenger trips increased by about 11 percent. Over the same period, annual average

[1] All levels of the government combined – federal, state, and local.
[2] National Transit Database data, available at http://www.ntdprogram.gov/ntdprogram/data.htm (accessed 03/18/2014); all levels of the government and all modes of transit included in the analysis; dollar amounts are not adjusted for inflation; inflation adjustment for the compound annual growth rate (CAGR) calculation uses data from the US Bureau of Labor Statistics available at http://www.bls.gov/data/inflation_calculator.htm (accessed 03/19/2014).
[3] The MAP-21 (Moving Ahead for Progress in the 21st Century) law was enacted in 2012 to authorize funding for federal highway and transit programs through fiscal year 2014.
[4] Figure from the MAP-21 report published by the American Public Transportation Association, available at http://www.apta.com/gap/legissues/authorization/Documents/APTA%20MAP-21%20Guide.pdf (accessed 03/19/2014).
[5] Refers to operations and maintenance.
[6] Previously the National Personal Transportation Surveys.

operating expense per vehicle revenue hour increased by 9.3 percent, operating expense per unlinked passenger trip increased by 11.5 percent, unlinked passenger trips per vehicle revenue hour decreased by 4.7 percent, and total subsidy per trip increased by 17.4 percent (NTD 2012; all cost figures are inflation-adjusted). Between 1990 and 2009, transit has consistently maintained an estimated mode share of less than 2 percent of all trips made in the US (Santos et al., 2011), and our analysis of the 2001 and 2009 NHTS shows that transit has lost share even in some of its largest markets[7] over the past decade.[8]

Given these trends, it is important to consider how public transit systems might attract more patrons and increase productivity. A recent analysis of US public transit policy suggests that strategies for efficiently increasing transit's market share must include investment in the dimensions of service quality that travelers value most (Giuliano, 2011). Using empirical evidence from Los Angeles, this paper explores whether investing in transit service reliability is meaningful.

1.2 Overview of research

Research exploring strategies that transit managers can adopt for promoting patronage is not new. Many studies analyzing travelers' attitudes and preferences have shown that service frequency, safety, comfort, fare level, speed, information availability, and both in-vehicle and stop/station level environmental quality influence transit travel demand (e.g. Taylor et al., 2009,

[7] We define "largest markets" as the top five Consolidated Metropolitan Statistical Areas (Census designated CMSAs included in the 2001 and 2009 NHTS) in terms of unweighted public transit trip share (public transit trips divided by total number of trips made by persons aged 5 and above in the sampled households on the NHTS designated travel day) in 2009 – authors' own analysis of NHTS data (publicly available at http://nhts.ornl.gov, last accessed November 14, 2013).

[8] Authors' analysis of 2001 and 2009 NHTS data available at http://nhts.ornl.gov (last accessed November 14, 2013); Percentage point change in unweighted public transit trip share (public transit trips divided by total number of trips made by persons aged 5 and above in the sampled households on the NHTS designated travel day) analyzed for New York (New York-Northern New Jersey-Long Island CMSA in NY-NJ-CT-PA), Washington D.C. (Washington-Baltimore CMSA in DC-MD-VA-WV), San Francisco (San Francisco-Oakland-San Jose CMSA in CA), Portland (Portland-Salem CMSA in OR-WA), and Pittsburg (Pittsburgh CMSA in PA). Note that transit mode share in Portland increased marginally by 0.23 percentage points

Iseki and Taylor, 2010; Eboli and Mazzulla, 2011; Lai and Chen, 2011; Cirillo et al., 2011; dell'Olio et al. 2011). Therefore, evidence suggests that interventions aimed at improving these quality attributes may help promote patronage.

Interestingly, although transit service reliability (referred to as "on-time performance" within the transit industry) is widely regarded as a critical component of service quality that affects the desirability of transit travel, we are unaware of any empirical research that analyzes the contribution of service reliability in determining patronage. We address this gap to inform transit policy.

In this paper, we fundamentally hypothesize that transit service reliability is a determinant of patronage; greater service reliability is assumed to attract greater patronage, all else equal, at times when travelers are expected to be particularly sensitive to travel time reliability. We perform a cross-sectional system-wide study of the Los Angeles Metro transit system using a unique historical archive of service supply, patronage, and performance data. By analyzing the variation in patronage across directional transit lines for weekday peak and off-peak periods, we estimate the marginal effect of service reliability. We build on existing transit patronage determination models, and adopt both an ordinary and a three-stage least-squares regression approach. Results support our hypothesis, and suggest a significant positive association between line reliability and line patronage, particularly in the weekday peak periods.

1.3 Policy implications

This paper provides first empirical evidence that transit service reliability affects patronage. Based on the research design, we conclude that reliable transit lines attract more patrons in part by inducing transit mode choice (in places where latent demand exists), and in part by influencing transit route selection (in transit-rich urban areas). It may therefore be plausible to expect some system-wide patronage gains from service reliability investments. Our research demonstrates that reliability investments may be cost-effective means of increasing productivity of transit lines and systems.

1.4 Paper structure

The remainder of this paper is organized as follows. Section 2 reviews theoretical literature on the concept of travel time reliability, and why transit service reliability should affect patronage. Section 3 introduces the conceptual models, and Section 4 describes our study area and data. Section 5 describes variables included in the regression models, and Section 6 presents the empirical models with discussions on findings. Finally, Section 7 presents conclusions, and policy implications.

2. Literature review

In this section, we present the theoretical basis for expecting a positive association between transit service reliability and patronage. We first summarize theory and past research highlighting the demand for reliable travel in general. We then explore why transit service reliability may influence demand for the transit mode. The review informs our conceptual model in Section 3.

2.1 Our demand for travel time reliability

Time is a scarce resource, and since travel time is generally unproductive, significant opportunity costs are associated with travel. The behavioral intent of minimizing travel time is long established (Jiang and Morikawa, 2004). But literature also suggests that travelers do not prefer traveling under unpredictable conditions; travel time unreliability adds additional costs and uncertainty. Travelers' perception of travel time reliability influences decisions regarding time of travel, destination choice, mode choice, and whether to travel at all (Fosgerau and Engelson, 2011).

Aversion for unreliability arises out of the consequences associated with arriving early or late at the destination (Small, 1982; Noland and Small, 1995; Noland et al., 1998). Early arrival may cause travelers to incur additional time costs as they wait for work to begin or offices to open; late arrival may cause penalties such as missed meetings or fines.

Since the formulation of the concept of schedule delay by Small (1982), researchers have used various experimental designs, theoretical frameworks, (un)reliability measures, and data sources to analyze how reliability might influence travel decisions (Carrion and Levinson, 2012, present an exhaustive review of literature). Past empirical research has focused largely on the automobile mode (including analysis of value pricing experiments), and has contributed to a better understanding of how the demand for reliable travel affects route choice (e.g. Noland et al., 1998; Lam and Small, 2001; Liu et al., 2004; Small et al., 2005; Asensio and Matas, 2008; Tilahun and Levinson, 2010), and trip scheduling (e.g. Small, 1982; various modifications to Small's scheduling model have been proposed and tested). Results generally suggest that travelers perceive expected travel time variation as a cost that is often more onerous than expected mean travel time. Therefore, risk-averse travelers may choose (also pay to travel along) relatively more predictable (e.g. lower probability of non-recurrent congestion) routes, and carefully choose travel time (including building in extra-time/time-cushion) in response to expected probabilities of travel time deviations. Although some studies (Bhat and Sardesai, 2006; Nam et al., 2005, and; Sweet and Chen, 2011) have shown that reliability influences mode choice as well, data constraints (e.g. unreliability of alternative modes traditionally captured through presentation of hypothetical scenarios in stated preference surveys, or by asking respondents of their past travel experiences) restrict evaluation of how objective improvements in mode-network reliability can affect mode choice. Sweet and Chen (2011) perform the best analysis of the reliability – mode choice relationship to our knowledge. The authors use GPS-based travel diary data from Chicago to measure unreliability of the auto network (and its spatiotemporal variation across the study area) to suggest that unreliability of the auto mode may induce transit mode choice.

2.2 The demand for transit service reliability

It is well known that patrons incur significant costs waiting (with or without real-time travel information) for transit, and arriving at the destination at an inconvenient time due to unreliable services. Therefore, the risk associated with transit (un)reliability should theoretically influence its demand relative to alternate travel modes. Patrons may also adjust routes and travel times to minimize expected risk.

We all hate to wait as part of a journey. Empirical evidence suggests that travelers value waiting time more than in-vehicle travel time or even walking time (Wardman, 2001; Wardman, 2004). For transit users, longer-than-expected wait times can result in even bigger penalties. As Rietveld et al. (2001) observe, most patrons travel via chains and make one or more transfers. Unreliability often results in missed connections – wait times get compounded and travel plans get jeopardized. Higher probability of schedule deviation (experienced or observed over time), and the resultant uncertainty leads to lower user confidence, attrition of risk-averse patrons, and prohibits choice riders from entering the market (Perk, et al., 2008).

Many qualitative attitudinal studies have underscored the demand for transit service reliability. For example, Iseki and Taylor (2010) observe that frequent and reliable service in a safe environment is important for transit users; Nurul Habib et al. (2011) find that transit users value "reliability and convenience" more than "ride comfort;" and Cantwell et al. (2009) find evidence that service reliability improvements can substantially benefit commuters. Among others, Bowman and Turnquist (1981), Furth and Muller (2006), and Casello et al. (2009) have emphasized the importance of transit reliability in determining transit travel demand. Reliability has been recognized as a critical attribute of transit service as early as the 1970s (e.g. Turnquist and Bowman, 1980). Researchers have since been exploring factors influencing transit reliability, developing quantifiable measures of service reliability (e.g. Polus, 1978; Chen et al., 2009), and exploring strategies to improve schedule adherence in an attempt to promote patronage.

We have not come across empirical research that estimates the effect of service reliability on transit use. Nevertheless, past studies help develop our conceptual models.

3. The conceptual model(s)

3.1 Hypothesis, unit of observation, and time period of analysis

In this research project, we select a slice of time (a "static" six-month time period between two consecutive transit service/schedule changes; a period when all service supply parameters were constant), and perform a cross-sectional examination of the Los Angeles Metro[9] transit system consisting of bus and rail lines.

We hypothesize that if service reliability influences the desirability of transit travel, then all else equal, a relatively more reliable transit line should theoretically attract greater number of users from within its service corridor. More choice riders may be drawn to that line, and patrons may choose the line among other potential alternatives. And this should be translated into relatively higher patronage of that line.

[9] Metro refers to the Los Angeles Metropolitan Transportation Authority.

Our unit of observation is a directional transit line. For example, Metro transit route 733 comprises of two directional lines – 733 East and 733 West. Note that routes have not been used as units of observation by aggregating/averaging across constituent lines. This is because lines in opposite directions serving the same route at a given time of the day generally have different service supply and performance characteristics due to the directional variation in travel demand and traffic patterns. Consequently, their patronage levels must also be different. Aggregation will therefore lead to loss of critical information.

The approach of using directional lines is certainly not perfect. Transit users often travel along chains and make one or more transfers. Consequently, and based on the hypothesis, it is possible that the service quality and performance of any one link in the chain will influence patronage of many associated links. Unfortunately, obtaining data on patronage along transit chains is difficult, if not impossible. We do not have access to such data. This limitation can influence study results. For example, a highly reliable bus line may have lower-than-expected patronage in part because a connecting line that is part of a potential travel chain is particularly unreliable.

Our analysis of the variation in patronage across directional lines focuses on weekday peak (AM peak between 6 AM and 9 AM, and PM peak between 3 PM and 7 PM) and off-peak (Mid-Day between 9 AM and 3 PM, and Night between 7 PM and 12 AM) periods. The time periods are defined by Metro for service planning purposes. Directional transit lines are hereafter referred to as "lines." Also, all analyses are performed for weekdays only.

3.2 Model forms

The conceptual model builds on theories of the determinants of aggregate transit service consumption or patronage (refer Taylor et al., 2009). Taylor et al. (2009) synthesize a very large volume of literature, and observe that aggregate consumption of public transit service depends upon the characteristics of travelers, metropolitan regions, substitute modes, and transit supply, with a high level of simultaneous association existing between transit supply and consumption.

We have developed two model forms: a single-stage linear model, and a simultaneous equations model. They are explained as follows:

I. The single-stage linear model

First, a single-stage linear model of transit line patronage is proposed. The basic assumption is that the observed variation in line-level patronage (or service consumption) is determined by the following parameter groups:

- Potential demand (consumed + latent) for transit use within the corridor that a line serves – this includes the sociodemographic and land use characteristics of the multi-modal transportation corridor traversed by a line
- Planned service supply characteristics of a line – this includes the physical characteristics of a line (e.g. en-route stops/stations), and the parameters that capture its planned service quality (e.g. service frequency or headway)
- Line service performance or (un)reliability[10]

The model (for time period of the day "*t*") can be conceived as:

$$\boldsymbol{P_{lt} = \beta_0 + \beta_1 D_{lt} + \beta_2 S_{lt} + \beta_3 R_{lt} + \varepsilon} \text{ ..... (Eqn. 1)}$$

Where: *P* is patronage/service consumption; *D* (potential demand) is a vector of corridor-level sociodemographic and land use measures; *S* (planned service supply) is a vector of line-level physical characteristics and planned level of service measures; and *R* is a vector of service (un)reliability measures, for line *l* at time period *t*. ε is the error term. Note that the parameter group *R* includes our explanatory variable(s) or variables of interest. Read "*t*" as AM peak, Mid-Day, PM peak, and Night.

[10] The term (un)reliability is used in general throughout the paper. While on-time performance is a measure of service reliability, early and late performances are measures of unreliability.

Detailed discussions about variable selection within each parameter group are included in Section 5. However, some potential concerns with the single-stage model form need to be clarified in advance. Note that (a) through (d) below correspond to theoretical connections/associations (dotted arrows) shown in Figure 1.

(a) Simultaneous relationship between service supply and patronage: Planned service supply characteristics of a line and its patronage at a given time period of the day must be highly correlated. While literature suggests that characteristics of service supply determine patronage, we know that transit agencies make supply-side adjustments[11] periodically[12] in response to observed demand or patronage. This simultaneity (statistically referred to as "endogeneity") creates difficulties in determining the direction of causal connection (service supply ⇆ patronage). Using results from a single-stage model (as in Eqn. 1), recommendations of service supply increases to boost patronage may therefore be untrustworthy[13]. This simultaneity, however, may or may not be a concern considering our research framework.

Argument 1: One argument is that the simultaneity problem may be ignored since the endogenous independent variable group (that includes variables measuring the planned service supply characteristics) is used as control in the model; biased (and possibly inflated) parameter estimates can be disregarded since no causal interpretations need to be made. Moreover, the reverse causality (patronage → service supply) may not be strong enough to pose a threat. Since transit service needs to satisfy broader policy goals[14] under constraints of limited resources[15], it is possible that service supply cannot perfectly respond to signals of consumption. The argument

[11] e.g. changes in service frequency, equipment allocation, etc. at different times of the day and days of the week.
[12] Generally in June and December every year for Metro transit lines.
[13] See Taylor et al. (2009) for detailed discussions; note that the authors directly addressed endogeneity, and found that supply-side increases can promote patronage at the aggregate level.
[14] e.g. providing basic service in particular areas regardless of patronage signals.
[15] e.g. revenue miles or revenue hours of service that can be allocated across the system.

implies that there are areas where transit service is under- or over-supplied. Argument 1 leads to estimation of what we refer to as the set of "OLS models" that are based on the structure of Eqn. 1. We understand, however, that ignoring the simultaneity effect can result in a mis-specified model overall.

Argument 2: Another argument is that it if signals of patronage influence service supply changes and resource reallocations for the most part, then parameter group "S" (or the endogenous variables within the group) should be dropped from Eqn. 1 altogether. Following this logic, we test a set of reduced-form "alternative OLS models."

Argument 3: The best approach, however, is to acknowledge the simultaneous relationship and employ appropriate statistical techniques to address it. Taylor et al. (2009) use the instrumental variables approach. We specify a full system of simultaneous equations and use the three-stage least-squares regression (3SLS) method. Our approach and its advantages are discussed in detail later in this section.

(b) Characteristics of alternative modes: Characteristics of substitute or alternative modes across the corridor that a transit line serves should theoretically influence its patronage. We have not directly included these characteristics (such as auto-mode congestion, parking availability and price, etc.) due to data constraints. We consider the sociodemographic and land use contexts traversed by a line (captured through measures such as corridor-level population and employment density) to serve as rough proxies for mode alternatives and their characteristics.

(c) Collinearity between potential demand and service supply: In the single-stage linear model form, it is possible that collinearity exists between parameter groups "D" and "S" (refer Eqn. 1) – greater the potential demand for transit use, greater/better is the level of service supply. This is not impossible in the cross-section, although the assumption may imply a very well-balanced spatial distribution of transit resources. Historically, transit investments and resource allocations must have been made (and new transit investments continue to be made) considering expected (or potential) transit travel demand; however, signals from actual consumption (or observed demand) and other policy priorities inform periodic service changes and continued investments.

Again, it is only fair to assume that the sum total of all transit services within a corridor is correlated to potential demand across the corridor; the unit of analysis in this case is a line.

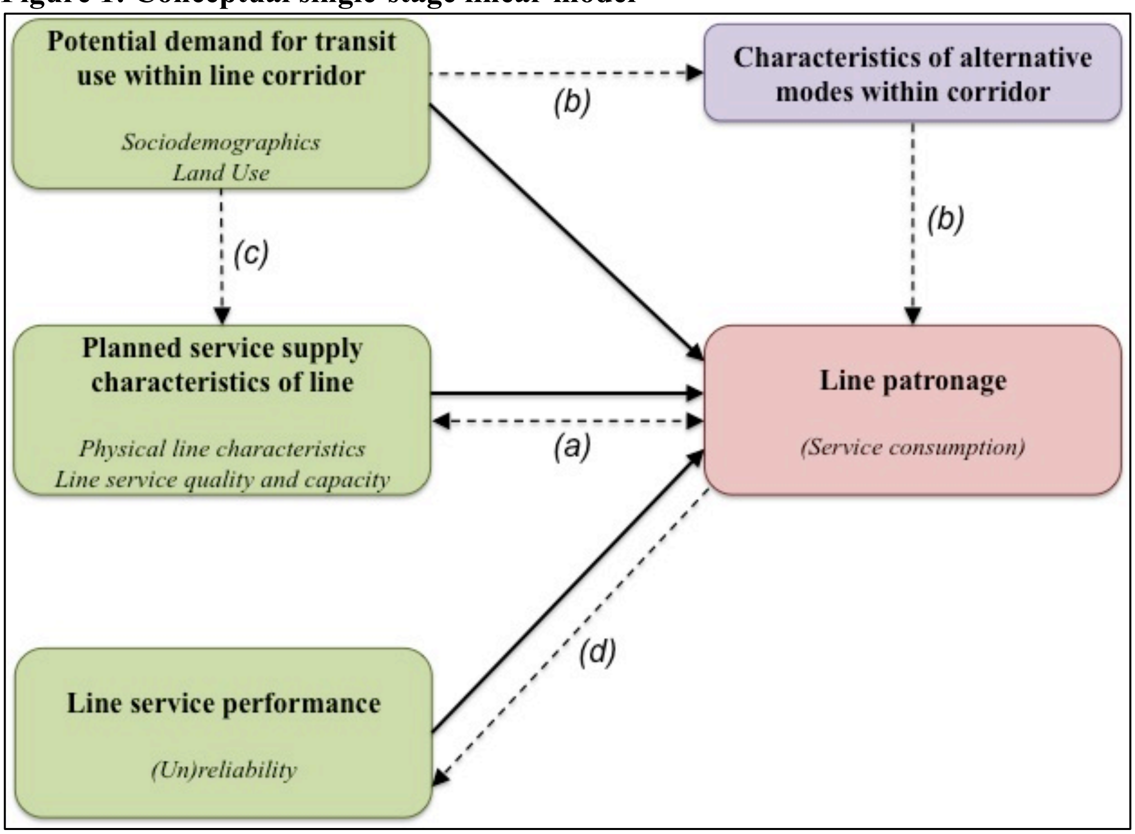
The conceptual model does not ignore the potential demand – service supply correlation altogether; in fact, the research design helps address the issue effectively. Since the unit of analysis is a line, two lines in opposite directions serving the same corridor traverse through the same geographic contexts, but many service supply characteristics (e.g. service frequency, equipment allocation, etc.) at a given time of day differ based on the predominant direction of passenger traffic flow. Therefore, the correlation does not exist, both theoretically and statistically, in our dataset. Supply-side variables have been selected carefully – to avoid any theoretical collinearity, but still capture potential demand and service supply characteristics appropriately.

(d) Exogeneity of service (un)reliability: Finally, is there any possibility that line-level patronage affects service (un)reliability? In theory, it can. However in practice, scheduling takes account of possible delays due to boardings and alightings in various volumes at various stops/stations along a line. In fact, Metro generally makes service changes twice every year, and schedule adjustments are made based on empirical evidence, often targeted towards improving on-time performance (and also for meeting a predetermined target). Therefore, it is unlikely that higher patronage will systematically "cause" unreliability or schedule deviation. However, idiosyncratic (or stochastic) fluctuations in boardings and alightings in the intermediate period between two service changes can contribute to unreliability. In this study, line unreliability is conceived of as the combined effect of many exogenous factors that cannot be accounted for in scheduling decisions.

Note that transit fares and information availability (that theoretically contribute to patronage/service consumption) do not enter into the model because they do not vary across Metro transit lines.

In sum, testing a conceptual single-stage linear model for investigating the transit service reliability – patronage connection seems useful. Figure 1 illustrates the model. Possible endogeneity and cross-correlation issues (explained above) are identified.

Figure 1: Conceptual single-stage linear model



Recall: Line refers to a transit route (bus or rail) in a given direction

II. The simultaneous equations approach

The simultaneous relationship between line-level service supply characteristics and patronage is best addressed by specifying a full set of simultaneous equations based on a theoretical understanding of the determinants of both transit service planning and patronage. In this approach, the two equations (for time period of the day "*t*") are conceived as:

$$\boldsymbol{S_{lt} = \alpha_0 + \alpha_1 P_{lt} + \alpha_2 Z_{lt} + \gamma} \text{ ....(Eqn. 2A)}$$

$$\boldsymbol{P_{lt} = \beta_0 + \beta_1 D_{lt} + \beta_2 S_{lt} + \beta_3 R_{lt} + \varepsilon} \text{ ..... (Eqn. 2B)}$$

Where: *P* is patronage/service consumption; *Z* is a vector of corridor-level factors that influence service planning in addition to signals of patronage; *D* (potential demand) is a vector of corridor-level sociodemographic and land use measures; *S* (planned service supply) is a vector of line-level physical characteristics and planned level of service measures; and *R* is avectort of service (un)reliability measures, for line *l* at time period *t*. γ and ε are the error terms. Note that the parameter group *R* includes our explanatory variable(s) or variables of interest. Read "*t*" as AM peak, PM peak, etc.

In theory, Eqn. 2A hypothesizes that regardless of observed levels of patronage, the level of service supply may be governed by other specific sociodemographic and geographic characteristics of the corridor served by a line, based on broader service planning priorities or even liabilities.

If an optimal level of service could proportionally be supplied across the network based only on signals of patronage, then transit systems could have avoided unproductivity and inefficiency. But the real world of transit planning and operations is far from ideal. And therefore our equation (2A) attempts at accommodating several practical possibilities. For example, the level of transit service supplied to relatively lower-income neighborhoods for providing basic accessibility, or to certain affluent (and/or low-density suburban) localities for promoting transit-orientation, may not be explained simply by observed patronage. Again, new services extended to areas with expected high latent demand due to particular sociodemographic profiles may be going through a transient (temporary unproductive) stage, waiting for patronage to pick up.

Moreover, it may not be possible to downgrade transit services in certain older parts of the city citing reasons of inefficiency. Also, a basic level of service is maintained across low-demand places and times to ensure seamless service. Finally, it is also possible that service is under-supplied in specific contexts; this may imply excessive loading and over-crowding on some transit vehicles at certain times of the day. Eqn. 2A therefore helps explain the existence of productive, break-even, and unproductive transit services.

Simultaneously, Eqn. 2B follows the structure of the single-stage Eqn. 1 to capture the various determinants of patronage. Variables under each parameter group are defined in Sections 5 and 6.

The set of simultaneous equations are estimated using the three-stage least-squares (3SLS) regression method that estimates all coefficients of the entire system simultaneously, and is a relatively more efficient method compared to a two-stage least-squares approach (Zellner and Theil, 1962). 3SLS accounts for the correlations of the errors across different equations of the system, and thereby improves the efficiency of estimates. We have used Stata[16] to estimate 3SLS models.

4. Study area and data sources

The current research focuses on the greater Los Angeles metropolitan region, and on the Metro system. Metro's network comprises of roughly 170 "primary" bus and rail routes, some or all of which are operational at particular time periods of the day and days of the week.

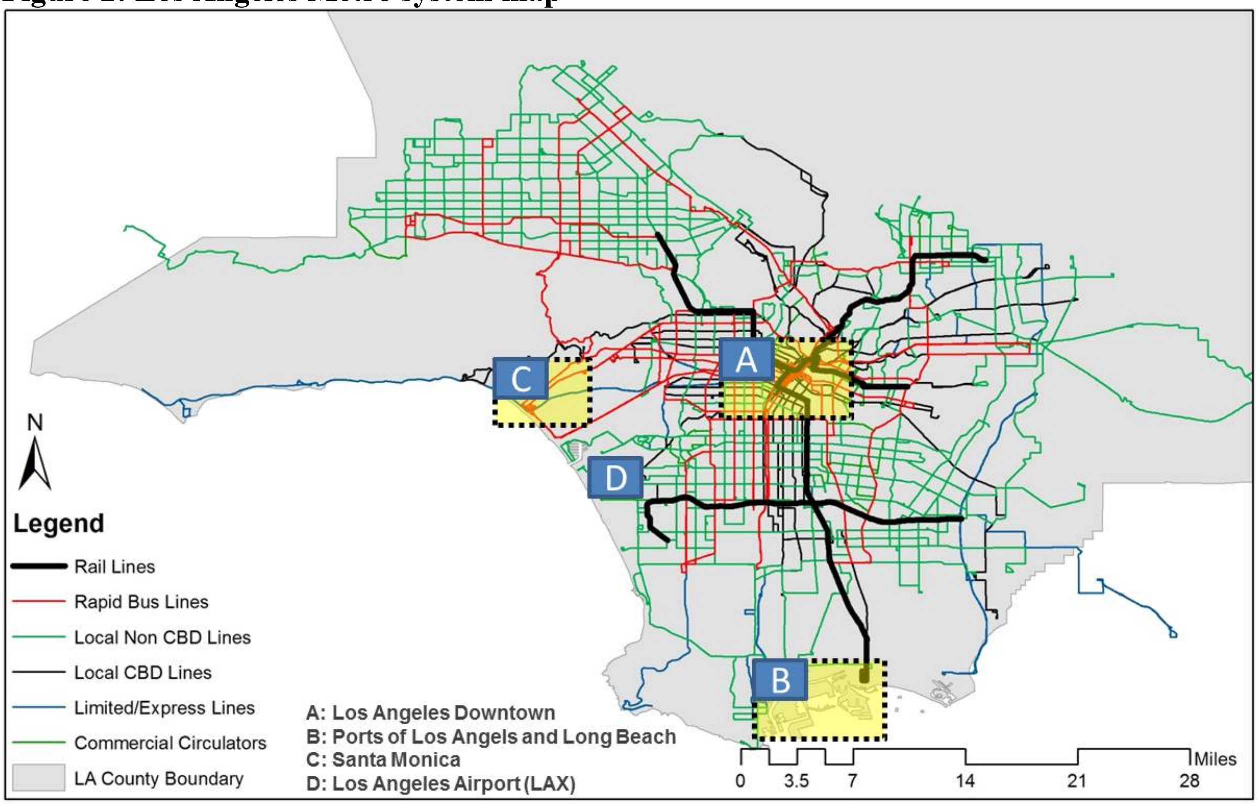
Over the past decade (2002-2011), Metro has expanded its service in terms of service area coverage (by 8 percent), annual vehicle revenue miles (by 21 percent), and annual vehicle

[16] Stata's technical note on the 3SLS regression method is available at http://www.stata.com/manuals13/rreg3.pdf (accessed 04/08/2014)

revenue hours (by 8 percent). However, transit ridership has increased just 3 percent (average weekday unlinked trips). Consequently Metro's productivity (cost per service hour, cost per passenger, passengers per service hour) has declined across all modes – bus, heavy rail, and light rail (all figures above are derived from NTD, 2002 and NTD, 2011).

The Metro transit system map including all bus and rail lines used in the study is shown in Figure 2.

Figure 2: Los Angeles Metro system map



Source: Metro (GIS shapefiles are available at developer.metro.net, and are updated periodically)
Note: Map corresponds to the June 2011 service change, and was valid between June 2011 and June 2012; Locations of landmarks are tentative, and intended for visual reference only.

Data from three principal sources has been used for this research: Metro transit data[17] available through the ADMS[18] research project; ACS (American Community Survey) 2007-2011

[17] This includes GIS-based data of bus/rail lines and stops/stations, and scheduled headways by line by time period of weekdays corresponding to the June 2011 service change; patronage data (boardings and alightings) by line by

data[19], and; SCAG (Southern California Association of Governments) employment and regional transit network data[20].

The cross-sectional analysis is conducted by aggregating and averaging patronage and performance/(un)reliability data by weekday peak and off-peak over a six-month period between December 2011 and May 2012. The aggregation/averaging operation helps smooth out seasonal fluctuations in patronage and performance. Moreover, perception regarding transit line performance is assumed (most likely) to develop over time through long-term experience or observation, which in turn is assumed to influence demand. We assume that long-term experience or observation of transit service performance (i.e. or on-time performance) is translated into a perception of the probability of service unreliability, which in turn is factored into the generalized cost of transit travel and hence influences transit mode choice or route/line choice. There is no prior literature on how users perceive and process performance over what length of time to make decisions or alter behaviors and patterns; perhaps an annual average works best, but we must be careful about the length of time used for aggregation/averaging. First, the period should not be too long so that we can expect regional socioeconomic, demographic, and land use parameters that collectively determine the potential demand for transit travel to be constant. Second, we must ensure that planned service supply is static over the period. Metro makes service changes twice a year that includes multiple service reorganizations and alterations

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stop/station by time period of weekdays, and; performance data (average early, on-time, and late performance as percentages) by line by time period of weekdays.

[18] ADMS (Archived Data Management System) is a Metro-funded research project involving the development and application of a historical archive of real-time multi-modal transportation system data from various agencies in the greater Los Angeles metropolitan region.

[19] Census tract level sociodemographic data (for computing line-corridor level measures) is collected from the American Community Survey 2007-2011 via Social Explorer (registered with the University of Southern California).

[20] GIS-based locations of firms (including employment of each firm), and transit routes and stops (all regional transit agencies) within the SCAG jurisdiction for 2008 are collected through a separate contract with SCAG.

in many dimensions of transit service that collectively influence patronage. The selected six-month time period ensures that system-wide Metro service supply is static[21].

5. Variables and descriptive statistics

5.1 Dependent variables

Metro generates average patronage data estimates, i.e. boardings and alightings, for each stop/station on each line by time period of day (i.e. peaks and off-peaks) and by day of week (weekdays and weekends). We use data for the six-month December 2011-May 2012 period, and then compute average *per-hour* total line boardings, for each line, for each time period of a typical weekday, to construct the dependent variables. The *per-hour* measures help compare the relative influences of the independent variables between the time periods consisting of unequal[22] number of hours.

Since the unit of analysis is a line, the derived six-month average patronage measure for bus line *"l"* corresponding to weekday time period *"t"* is computed as:

$$(\boldsymbol{Average\ per\ hour\ boardings})_l^t = \frac{\mathbf{1}}{\boldsymbol{M}} \sum_{\boldsymbol{m=1}}^{\boldsymbol{M}} \left[\sum_{\boldsymbol{s_l}} \frac{\boldsymbol{B_{s_l}^{tm}}}{\boldsymbol{h_t}} \right]$$

Where $B_{s_l}^{tm}$ is the estimated average boardings at stop *s* on line *l* during time period *t* of month *m* (available from Metro); h_t is the number of hours within time period *t* (e.g. h_t = 3 for the weekday AM peak, and 4 for weekday PM peak); *m* denotes month, and takes discrete values *(1,2,...,M)* for the six months December 2011 through May 2012 (*M*=6 for our study). Read "*t*" as AM peak, Mid-Day, PM peak, and Night period of weekdays.

For rail lines, average estimates of weekday period-wise boardings and alightings at each station on each line corresponding to the six-month study period are directly available. The computation method for deriving the average patronage measure for rail is comparable to bus

[21] Note that Metro service change in June 2011 was followed by the June 2012 shake-up.
[22] Weekday AM peak = 6 AM to 9 AM; Mid-Day = 9 AM to 3 PM; PM peak = 3 PM to 7 PM; Night = 7 PM to 12 AM.

lines – only without the six-month averaging operation. Note that there were no service changes for the Metro rail system within the study period.

The dependent variables, although primarily derived out of raw boarding counts, are averaged at multiple levels (first by Metro, and then by the authors) from monthly/yearly estimates, and therefore can be considered to be continuous. Descriptive statistics are given in Table 2.

5.2 Explanatory variables

For a given trip, a transit vehicle is supposed to arrive at all specified "timepoints" (usually at designated stops/stations) along its route within a certain range around the scheduled time. For a given trip, if a vehicle arrives at a particular timepoint more than one minute early, or more than five minutes late with respect to the scheduled time, then it is considered to be "early" or "late" respectively; else, it is considered to be "on-time," or that it has adhered to its schedule. The extent of "earliness" or "lateness" is not considered for computing aggregate performance measures. Vehicles fitted with GPS devices are tracked in real-time for recording schedule adherence/deviation data; all trips for all vehicles, bus and rail, are tracked. Subsequently, data is processed (aggregated/averaged) to derive average line-level (and system-wide) ISOTP or "in service on-time performance" estimates expressed as early, on-time, and late percentages.[23]

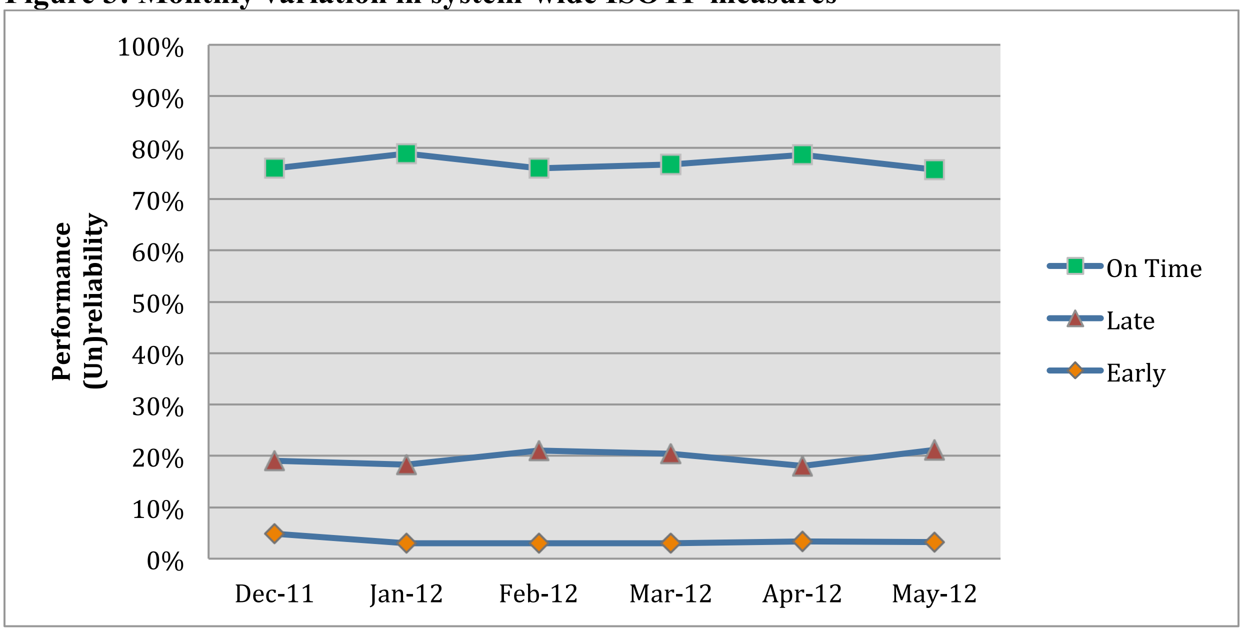
ISOTP measures used in this research are at a finer level of temporal resolution – by time period of weekdays. We have aggregated and averaged line level ISOTP measures (by time period of weekday) over the six-month time frame. The three ISOTP measures are referred to as

[23] For example, a line with an average on-time performance of 80 percent over a particular month (meaning that vehicles on that line have adhered to timepoint schedules 80 percent of the time over the month) has a greater reliability than another with an average on-time performance of 70 percent; similarly, a line with an average late performance of 20 percent has a greater unreliability than another with an average late performance of 10 percent, holding early performance constant.

(un)reliability measures, since while on-time performance is a measure of line/system reliability, early and late performances are measures of unreliability.

Let us first inspect the monthly variation in (un)reliability measures within the study period at the system level (all Metro bus and rail lines combined). Figure 3 plots the system-wide average weekday on-time, early, and late service performances by month over the study period. System (un)reliability shows little variation, with on-time performance ranging between 76 and 79 percent. Transit vehicles more often run behind schedule (vehicles run late, i.e. they are more than 5 minutes late at timepoints, around 20 percent of the time on an average) than ahead of it (vehicles run early, i.e. they are more than 1 minute early at timepoints, less than 5 percent of the time on an average).

Figure 3: Monthly variation in system-wide ISOTP measures



Source: Metro Service Performance Analysis website (http://isotp.metro.net)

The unit of analysis for this study, however, is a transit line. Six-month average (un)reliability measures for bus line *"l"* corresponding to weekday time period *"t"* is derived as:

$$[\boldsymbol{Average\ (Un)reliability\ Measure}]_l^t = \frac{\boldsymbol{1}}{\boldsymbol{M}} \sum_{\boldsymbol{m=1}}^{\boldsymbol{M}} \boldsymbol{P_l^{tm}}$$

Where: Average (un)reliability measure is expressed as early (percent expressed as decimal), on-time (percent expressed as decimal), or late (percent expressed as decimal) performance; P_l^{tm} is the estimated average (un)reliability measure (early/on-time/late) for line *l* during time period *t* of month *m* (available from Metro); *m* denotes month, and takes discrete values (*1,2,...,M)* for the six months December 2011 through May 2012 (*M*=6 for our study); Percentages are expressed as decimals in the dataset used, and should be read accordingly throughout the paper. Read "*t*" as AM peak, Mid-Day, PM peak, and Night period of weekdays.

Note that for the rail network, average line-level (un)reliability data corresponding to the six-month study period are directly available.

5.3 Other (control) variables

Based on the conceptual model frameworks (refer Section 3), control variables under each control parameter group are selected (Table 1). Variable selection is, in part, guided by the Taylor et al. (2009) study, and also based on a theoretical understanding of factors associated with mode choice/use (e.g. Badoe and Miller, 2000).

Table 1: Control variables

Variable	**Construction/Measurement (Data source)**
Potential demand for transit use within line corridor: Corridor-level sociodemographics-land use-connectivity measures, denoted by "D" in the conceptual models	
Mean population density	Stop/station weighted mean of the population densities (persons per sq. mi.) of all census tracts traversed by a line. (ACS 2007-2011)
Mean income	Stop/station weighted mean of median incomes (in 2010 inflation adjusted dollars) of all census tracts traversed by a line. (ACS 2007-2011)
Unemployment	Stop/station weighted mean of the unemployment rates (percent of population 16 years and over unemployed) of all census tracts traversed by a line. (ACS 2007-2011)
No-vehicle households	Stop/station weighted mean of the proportion of no-vehicle (carless) households (percent households with no vehicles) of all census tracts traversed by a line. (ACS 2007-2011)
Employment accessibility	Total number of employments per unit length of a line; Measured as total jobs within quarter-mile buffer (either side) of a bus line or the sum of total jobs within quarter-mile radius of all stations for a rail line, divided by line length. (2008 employment data from SCAG)
Transit alternatives	Count of all stops served by non-Metro transit operators within quarter-mile buffer (either side) of a bus line, or sum of the counts of all stops served by non-Metro transit operators within quarter-mile radius of all stations for a rail

	line. (2008 regional transit service data from SCAG)
Planned service supply characteristics of line – denoted by "S" in the conceptual models	
Total stops/stations	Count of total stops/stations for a line. (June 2011 service change data from Metro)
Stops/stations per mile	Count of total stops/stations per unit length of a line. (June 2011 service change data from Metro)
Scheduled headway	Scheduled headway (line level average; in minutes) of a line. (June 2011 service change data from Metro)
Line capacity	Average number of "standard" cars per equipment serving a line. Bus lines are considered to have a capacity of 1 (note that both rapid as well as local lines can have some articulated buses in service at certain times of the day; we do not have detailed bus equipment data); rail lines have capacity >1. (June 2011 service change data from Metro)
Factors affecting service supply characteristics of line – denoted by "Z" in Eqn. 2A	
Mean income, Unemployment, No-vehicle households	See description above.
Mean neighborhood gross rent	Stop/station weighted mean of the median gross rents (in 2010 inflation adjusted dollars) of all census tracts traversed by a line. (ACS 2007-2011)
Mean age of neighborhood	Stop/station weighted mean of the median housing structure age (as in 2012) of all census tracts traversed by a line. (ACS 2007-2011)

Note: "Vehicle revenue hours" is not included as a measure of planned service supply[24]

Note that final variable selection has been influenced by analysis of cross-correlations among independent variables used in regressions (Section 6). Many other control variables were considered but finally dropped for developing efficient models. Our final regression models are not expected to have multicollinearity bias.

5.4 Descriptive statistics

Summary statistics of variables used in regression models are given in Table 2. There are several observations to be drawn about the Metro system.

First, there is great variation in average hourly line boardings – both across time periods and across lines within each time period. Peak-period patronage is significantly higher than the

[24] Planned service supply is commonly measured in terms of vehicle revenue hours (RVH). We could not directly test the RVH variable, since we could not obtain line-level RVH data for each time period of the weekday separately (only daily total route level data for typical weekdays, Saturdays, and Sundays are available). RVH, however, may not be the most relevant measure considering our model frameworks. We have included (directly or via proxy) those components of RVH that influence patronage, such as scheduled headway, operating speed, and per-vehicle capacity.

off-peak with boarding numbers dropping sharply after 7 PM. Transit activity is highest in the PM peak and lowest at night.

Second, buses and trains run ahead of schedule only about 2-3 percent of the time on average; earliness is therefore a rare occurrence. Interestingly, on-time performance seems to be best during the AM peak. At other times of the day, vehicles run behind schedule around 20-25 percent of the time. High service unreliability during the highly congested PM peak is expected, but poor system-wide performance at night is surprising.

Third, on average, Metro transit lines serve corridors with very high population density and high percentage of no-vehicle households; they also provide very high employment accessibility. This suggests high potential transit demand in the Metro service area. However, the average scheduled headway is quite long (over 20 minutes) even during the peak. Long headways are inconsistent with high potential demand.

Finally, the large variation in the variables of interest is expected to help derive meaningful conclusions from the regression models.

Table 2: Descriptive statistics
Unit of observation: Metro transit (bus or rail) line

Variable			**N**	**Mean**	**SD**	**Min**	**Max**	**Median**
Average per-hr boardings								
	Peak	*AM Peak*	284	323.36	531.69	0.00	5096.81	194.67
		PM Peak	288	364.46	632.03	0.00	6106.12	208.25
	Off-peak	*Mid-Day*	291	272.81	411.50	0.00	3922.96	164.50
		Night	291	82.45	157.21	0.00	1342.29	33.00
Average early performance								
	Peak	*AM Peak*	273	0.03	0.03	0.00	0.26	0.03
		PM Peak	277	0.03	0.04	0.00	0.47	0.03
	Off-peak	*Mid-Day*	279	0.03	0.02	0.00	0.17	0.03
		Night	275	0.02	0.03	0.00	0.23	0.02
Average late performance								
	Peak	*AM Peak*	273	0.13	0.07	0.00	0.37	0.12
		PM Peak	277	0.25	0.11	0.00	0.62	0.25
	Off-peak	*Mid-Day*	279	0.20	0.11	0.00	1.00	0.19
		Night	275	0.25	0.14	0.00	1.00	0.24
Mean population density (persons per sq. mi.)			291	12889	4318	2057	28630	12379
Mean Income (2010 dollars)			291	53314	16205	26656	109245	53006
Unemployment (%)			291	6.47	1.12	0.50	11.85	6.55
No-vehicle households (%)			291	13.71	6.65	0.65	30.70	12.08
Employment accessibility (no.)			289	13733	12748	588	60283	7993
Transit alternatives (no.)			291	543	517	14	2548	349
Total stops/stations (no.)			291	68	35	5	164	67
Stops/stations per mile (no.)			289	4.13	1.83	0.16	11.03	4.29
Scheduled headway (min)								
	Peak	*AM Peak*	282	23.06	15.58	5.00	90.00	18.00
		PM Peak	286	24.01	16.97	5.00	90.00	18.00
	Off-peak	*Mid-Day*	285	40.00	58.22	6.00	360.00	25.71
		Night	289	69.44	72.85	7.70	360.00	45.00
Mean neighborhood gross rent (2010 dollars)			291	1189	197	885	1892	1177
Mean age of neighborhood (years till 2012)			291	53	6	35	63	53

Note: Data for all parameters are not available for all lines; “Average” refers to average over the six-month study period; Weekdays are considered only.

6. Analysis of the transit (un)reliability – patronage connection: Models and discussions

In this section, we present findings of the regression models of average per-hour line boardings for weekday peak (observations in the AM and PM peaks are pooled) and off-peak (observations for the Mid-Day and Night periods are pooled) periods. Only those lines for which complete information (corresponding to all included variables) is available have been included in the analyses.

First, models are estimated for bus lines only (Section 6.1). This is primarily because of rail lines constitute a very small number of observations, and also since rail may be considered to be an altogether different system. Analysis of the Metro bus system, however, is followed by an analysis of bus and rail lines combined (Section 6.2).

6.1 Regression models including bus lines only

6.1.1 Single-equation OLS regression models

Under the linear single-equation framework (see Eqn. 1), we first estimate OLS (ordinary least-squares) regression models (Models 1 and 2 in Table 3) of average per-hour bus line boardings for the peak and off-peak periods. Note that time-period indicator variables are included to capture structural differences in transit travel demand and patterns across time periods included within the designated peak and off-peak.

Measures of service unreliability, rather than reliability, have been included in the models. As explained in Section 5.2, measures of unreliability are line-level average early and late performance. Both unreliability measures may be included together since they are mutually exclusive.

Table 3: Simple OLS models of bus line patronage
Dependent variable: Average per-hour bus line boardings (patronage measure)

Variable	Weekday Peak (Model 1)			Weekday Off-Peak (Model 2)		
	Parameter estimate	Pr>|t|	Std. estimate	Parameter estimate	Pr>|t|	Std. estimate
Potential demand within corridor						
Mean population density	0.0261	0.00	0.4463	0.0220	0.00	0.5203
Mean income	0.0008	0.23	0.0539	0.0014	0.02	0.1224
Unemployment rate	20.6601	0.00	0.0954	7.7235	0.18	0.0467
No-vehicle households	-1.5490	0.47	-0.0419	-0.3002	0.87	-0.0110
Employment accessibility	0.0012	0.28	0.0590	0.0028	0.00	0.1990
Transit alternatives	0.0354	0.16	0.0754	0.0176	0.41	0.0501
Planned line service supply						
Total stops	2.8400	0.00	0.3910	2.1366	0.00	0.3918
Stops per mile	-31.3017	0.00	-0.2271	-24.5626	0.00	-0.2390
Scheduled headway	-7.3064	0.00	-0.4852	-0.3346	0.00	-0.1141
Line unreliability (Percent expressed as decimal)						
Early	148.0091	0.59	0.0141	95.7491	0.68	0.0125
Late	-146.0823	0.05	-0.0644	-85.6640	0.08	-0.0558
Time-period indicator for Model 1 (Ref=AM peak)						
PM Peak	51.5820	0.00	0.1057			
Time-period indicator for Model 2 (Ref=Mid-Day)						
Night				-149.7674	0.00	-0.4097
Intercept	-148.5845	0.08	.	-244.3103	0.00	.
N		532			535	
Adjusted R-square		0.68			0.56	

Note: Unit of observation is a directional Metro bus line

Results of Models 1 and 2 suggest that the directions of influence of the independent variables are generally consistent with expectation. For example, corridor-level mean population density has a statistically significant positive association with line patronage, all else equal. Planned service supply and patronage of lines are highly associative – lines with greater number of stops and higher service frequency (i.e. shorter headway) have significantly higher patronage during both peak and off-peak periods, all else equal; however, frequent stop-making (i.e. lines with more stops per unit route mile) negatively affects patronage. On an average, there is greater per-hour system-wide patronage in the PM peak compared to the AM peak, and over the mid-day compared to night. Interestingly, lines serving relatively higher-income neighborhoods have greater patronage, all else equal, during the off-peak period; no such income effect is observed during the peak. This may suggest that many higher-income patrons have flexible schedules, or that choice-riders are attracted during the relatively lower-volume off-peak period. Note that the lack of statistical significance of the employment accessibility variable in the peak period is surprising.

Although potential demand and planned supply variables explain a large part of the variation in patronage across lines, there is evidence that line service unreliability (specifically late performance) is negatively associated with patronage during both peak and off-peak; the effect sizes are modest but statistically significant (albeit only at the 90 percent confidence level during the off-peak period). This suggests that lines with lower probability of running behind schedule attract more patronage, all else equal. It seems that the observed effect is due to risk-averse patrons avoiding unreliable lines, and/or choice-riders drawn to relatively more reliable lines. Also, service unreliability is more onerous, on average, during the peak.

Per model estimates, early performance (i.e. frequency of early arrivals at scheduled timepoints, or running ahead of the schedule) does not have any significant influence on patronage. This is not surprising, and it does not necessarily imply that earliness is less onerous than lateness. First, it is possible that early performance does not matter since the average earliness (i.e. considering those instances when buses run early) for most observations in the dataset is close to (obviously lower than) -1.0 min with respect to schedule; or that on an average earliness seldom results in missing a bus. There is no way to verify this. In any case, earliness is a rare occurrence, and thus it is plausible that it has no effect on patronage. On the other hand, a bus must run late by at least 5 minutes to be considered late. We have no information on the distribution of actual lateness, but it is reasonable to assume that late buses result in longer-than-expected wait times, and may also cause passengers to miss transfer connections. Second, recall that earliness or lateness is measured from arrival data at designated timepoints on lines. If a bus arrives early at a timepoint, it often dwells (or lays over), and departs only at the scheduled time. Therefore, for patrons, earliness may or may not result in missing a bus.

6.1.2 Alterative (single-equation) OLS regression models

Next, we estimate alternative OLS models (Models 3 and 4) of bus line patronage by dropping the headway variable, under the assumption that service frequencies are largely determined by, and changed in response to, patronage data (refer Section 3.2 for rationale). Table 4 summarizes model results.

Note that the effect sizes and statistical significances of the service unreliability variable (late performance; for both peak and off-peak) increase once the potentially endogenous regressor is excluded. Also, employment accessibility and income emerge as a significant determinant of patronage in the peak period. Our model is sensitive to the headway variable, and therefore testing the simultaneous equations method seems appropriate.

Table 4: Alternative OLS models of bus line patronage

Dependent variable: Average per-hour bus line boardings (patronage measure)

Variable	Weekday Peak (Model 3)			Weekday Off-Peak (Model 4)		
	Parameter estimate	Pr>|t|	Std. estimate	Parameter estimate	Pr>|t|	Std. estimate
Potential demand within corridor						
Mean population density	0.0338	0.00	0.5776	0.0228	0.00	0.5386
Mean income	0.0016	0.05	0.1058	0.0015	0.01	0.1335
Unemployment rate	18.2798	0.02	0.0844	9.9765	0.08	0.0609
No-vehicle households	2.7049	0.30	0.0731	0.2302	0.90	0.0084
Employment accessibility	0.0049	0.00	0.2499	0.0032	0.00	0.2285
Transit alternatives	0.0142	0.64	0.0303	0.0153	0.48	0.0436
Planned line service supply						
Total stops	4.2399	0.00	0.5837	2.4185	0.00	0.4431
Stops per mile	-53.3513	0.00	-0.3871	-27.6804	0.00	-0.2689
Line unreliability (Percent expressed as decimal)						
Early	-36.7829	0.91	-0.0035	101.6621	0.66	0.0133
Late	-259.2716	0.00	-0.1143	-108.4996	0.02	-0.0734
Time-period indicator for Model 3 (Ref=AM peak)						
PM Peak	57.0962	0.00	0.1170			
Time-period indicator for Model 4 (Ref=Mid-Day)						
Night				-155.5285	0.00	-0.4259
Intercept	-523.3367	0.00	.	-304.6803	0.00	.
N		532			538	
Adjusted R-square		0.52			0.55	

Note: Unit of observation is a directional Metro bus line

6.1.3 Simultaneous equations models

Two equations are formulated following the model framework proposed in Eqn. 2A and Eqn. 2B. In the context of our study, the scheduled headway variable and the patronage (average per-hour bus line boardings) variable are assumed to be endogenous.

First, line-level scheduled headway is modeled as a function of its patronage along with select variables (corridor-level sociodemographic profiles and neighborhood characteristics) that are expected to capture factors affecting transit service planning (see Section 3.2 for rationale, and Table 1 for variable definitions). Second, line-level patronage is modeled as a standard function of potential demand, service supply, and unreliability parameters. The 3SLS regression results for the weekday peak and off-peak periods are summarized in Table 5.

Results from Models 5 and 6 suggest that patronage drives service frequency (more patronage associated with shorter headway) during both peak and off-peak. However, the converse is unclear. Our dataset from the Los Angeles Metro bus system does not help conclude whether service frequency is a significant determinant of patronage. Therefore, the extent to which further increases in bus service frequency will result in patronage gains is uncertain.

Table 5 confirms that service unreliability (again, late performance) is a significant determinant of bus line patronage during the peak period. On an average, and all else equal, a 10-percentage point lower late performance is associated with a higher patronage of about 9 percent. The effect is modest, but may not be inconsequential from a policy perspective.

The models highlight other key issues. First, bus lines traversing corridors with relatively higher gross rents have higher peak-period service frequencies on an average, holding patronage and other factors constant. This provides evidence of supply-consumption mismatch for at least some bus lines. Second, the negative coefficient of the "no-vehicle households" parameter (in the first equation) in the peak period may imply self-selection of individuals without cars (or individuals with pro-transit attitudes) into neighborhoods with good bus transit access. Third, rapid buses that skip stops and have higher average service speeds seem to attract more peak-period patronage, all else equal. Finally, population density is the single significant determinant of weekday off-peak bus transit patronage; in general, the variation in corridor-level population density explains a large fraction of the variation in patronage across bus lines.

Table 5: Three-stage least-squares (simultaneous equations) models of bus line patronage

Variable	Weekday Peak (Model 5)			Weekday Off-Peak (Model 6)		
	Parameter estimate	**P>z**	**Std. estimate**	**Parameter estimate**	**P>z**	**Std. estimate**
First Equation: Dependent variable – Scheduled headway						
Endogenous patronage variable						
Average per-hour bus line boardings	-0.0415	0.00	-0.6240	-0.1908	0.00	-0.5590
Corridor sociodemographic profile						
Mean income	0.0001	0.39	0.0840	-0.0004	0.47	-0.1010
Unemployment rate	1.7478	0.00	0.1220	-3.3007	0.20	-0.0580
No-vehicle households	-0.5352	0.00	-0.2180	-0.6546	0.32	-0.0700
Corridor neighborhood characteristics						
Mean neighborhood gross rent	-0.0140	0.03	-0.1730	0.0174	0.64	0.0560
Mean age of neighborhood	0.0512	0.39	0.0180	0.1682	0.76	0.0150
Intercept	40.2132	0.00	.	103.2407	0.04	.
N		532			535	
Adjusted R-square		0.53			0.16	
Second Equation: Dependent variable – Average per-hour bus line boardings						
Potential demand within corridor						
Mean population density	0.0220	0.00	0.3770	0.0202	0.00	0.4780
Mean income	0.0002	0.87	0.0120	0.0012	0.21	0.1080
Unemployment rate	26.1090	0.00	0.1210	6.5651	0.65	0.0400
No-vehicle households	-2.0375	0.64	-0.0550	-0.3096	0.92	-0.0110
Employment accessibility	0.0048	0.11	0.2450	0.0027	0.23	0.1940
Transit alternatives	-0.0061	0.77	-0.0130	0.0148	0.52	0.0420
Planned line service supply						
Total stops	3.1153	0.01	0.4290	2.0600	0.15	0.3780
Stops per mile	-40.8576	0.03	-0.2960	-23.5745	0.15	-0.2290
Scheduled headway *(endogenous)*	-6.8917	0.27	-0.4580	-0.6531	0.73	-0.2230
Line unreliability (Percent expressed as decimal)						
Early	-281.6727	0.26	-0.0270	77.6654	0.75	0.0100
Late	-229.4909	0.04	-0.1010	-84.0993	0.35	-0.0550
Time-period indicator for Model 5 (Ref=AM peak)						
PM Peak	32.4853	0.00	0.0670			
Time-period indicator for Model 6 (Ref=Mid-Day)						
Night				-138.4870	0.00	-0.3790
Intercept	-66.7370	0.84	.	-189.1725	0.58	.
N		532			535	
Adjusted R-square		0.67			0.56	

Note: Unit of observation is a directional Metro bus line

6.2 Regression models including bus and rail lines

Bus and rail are two different systems, and rail lines are indeed outliers in our dataset. The 16 rail observations per period (weekday peak and off-peak) have very high patronage levels (over 10 times higher on average than bus observations in the peak and off-peak respectively) and exceptionally high on-time performance (close to 100 percent). It is therefore possible that including rail lines will create bias in favor of the unreliability parameters.

In order to avoid bias, we use additional statistical controls. We add a "line capacity" variable (refer Table 1 for definition) to the set of variables used in the bus-only analysis (Section 6.1). We also include a rail line indicator variable that takes the value "1" for a directional rail line and "0" otherwise. The indicator variable is definitely too restrictive, but it allows us to capture the many unobserved factors that determine rail travel demand (such as on-board and station-level comfort, safety, and amenities), and also account for the difference between bus and rail systems.

The simple and alternative single-equation OLS regression models of weekday peak/off-peak period average per-hour bus/rail line boardings are not presented in this paper. Results of the robust 3SLS (simultaneous equations) regression model are summarized in Table 6.

Models 7 and 8 also demonstrate that transit service unreliability (late performance, as expected) is a significant (at the 90 percent confidence level) predictor of peak-period patronage at the line level.

The loss of statistical significance of the unreliability parameter after including rail observations can be attributed to the rail line indicator variable. Estimating the same models without the indicator variable substantially inflates the magnitude and significance of the unreliability parameter and strengthens our hypothesis; however, this leads to bias due to the many (unobserved) omitted variables that influence rail travel demand, and that distinguish between bus and rail lines. We do not present models without the indicator variable. We accept that Models 7 and 8 are not effective enough for isolating the marginal influence of service (un)reliability on Metro's system-wide patronage.

The parameter estimate of the indicator variable is valuable in itself. It shows that on average, and all else equal, Metro rail attracts significantly greater patronage than Metro bus. But again, the extent to which this effect can be attributed to rail's near-perfect on-time performance is unclear. Also, one should not generalize that rail is more effective than bus in promoting patronage. It is possible that the Los Angeles Metro rail system is appropriately planned along corridors most primed for rail investments; consequently patronage is high. Therefore, it is reasonable to infer that rail lines extended to areas with high latent demand that significantly increase regional accessibility will help promote patronage.

Table 6: Three-stage least-squares (simultaneous equations) models of bus/rail patronage

Variable	Weekday Peak (Model 7)			Weekday Off-Peak (Model 8)		
	Parameter estimate	**P>z**	**Std. estimate**	**Parameter estimate**	**P>z**	**Std. estimate**
First Equation: Dependent variable – Scheduled headway						
Endogenous patronage variable						
Average per-hour line boardings	-0.0050	0.00	-0.1820	-0.0648	0.00	-0.3470
Corridor sociodemographic profile						
Mean income	0.0002	0.10	0.2180	-0.0005	0.36	-0.1230
Unemployment rate	1.6660	0.00	0.1160	-2.9231	0.25	-0.0520
No-vehicle households	-1.0203	0.00	-0.4140	-1.5518	0.01	-0.1680
Corridor neighborhood characteristics						
Mean neighborhood gross rent	-0.0216	0.01	-0.2630	0.0213	0.58	0.0680
Mean age of neighborhood	0.0028	0.98	0.0010	-0.3467	0.53	-0.0320
Intercept	41.8786	0.00	.	123.0883	0.01	.
N		548			551	
Adjusted R-square		0.28			0.11	
Second Equation: Dependent variable – Average per-hour line boardings						
Potential demand within corridor						
Mean population density	0.0328	0.00	0.2360	0.0257	0.00	0.3410
Mean income	0.0002	0.91	0.0040	0.0026	0.01	0.1240
Unemployment rate	31.6489	0.01	0.0600	21.6442	0.10	0.0720
No-vehicle households	-15.8391	0.02	-0.1760	0.7815	0.83	0.0160
Employment accessibility	0.0031	0.53	0.0660	0.0036	0.14	0.1390
Transit alternatives	0.0238	0.55	0.0210	0.0057	0.87	0.0090
Planned line service supply						
Total stops/stations	3.5933	0.06	0.2070	3.7339	0.01	0.3850
Stops/stations per mile	-43.7194	0.14	-0.1350	-9.3607	0.52	-0.0520
Scheduled headway *(endogenous)*	-15.9005	0.10	-0.4350	1.5144	0.40	0.2830
Line capacity	859.9838	0.00	0.4960	448.3262	0.00	0.5130
Rail line indicator (=1 if rail)	1325.2150	0.00	0.3760	815.9686	0.00	0.4130
Line unreliability						
(Percent expressed as decimal)						
Early	-251.4918	0.56	-0.0100	-360.6644	0.31	-0.0260
Late	-297.5850	0.09	-0.0560	-152.7216	0.12	-0.0570
Time-period indicator for Model 7						
(Ref=AM peak)						
PM Peak	75.0612	0.00	0.0630			
Time-period indicator for Model 8						
(Ref=Mid-Day)						
Night				-219.1315	0.00	-0.3310
Intercept	-720.2585	0.12	.	-1158.637	0.00	.
N		548			551	
Adjusted R-square		0.88			0.67	

Note: Unit of observation is a directional Metro bus or rail line

6.3 Limitations

Our study of the Los Angeles Metro system generally indicates a statistically significant positive association between transit line reliability and line patronage in the weekday peak period. Therefore, reliability seems to drive patronage, at least in part. Although our hypothesis is supported, there are several limitations that influence policy recommendations.

First, we are unsure of the extent to which results can be generalized. We must recognize that Los Angeles is uniquely primed for both transit service provision and consumption. The high regional population and employment density, ethnic diversity, poverty, and alarming peak-period traffic congestion collectively contribute to high latent demand for good-quality transit service. Los Angeles Metro, along with many other local operators, already provides extensive transit service coverage of reasonably good quality. Consequently, we might expect that strategic improvements in transit service reliability will more effectively attract patronage in Los Angeles than many other urban areas.

Second, our study cannot effectively predict the extent to which reliability improvements would result in system-wide patronage gains. Disproportionate increase in reliability across lines may lead to some redistribution of patronage. This means that existing patrons may shift from one line or route to another for ensuring relatively more reliable travel. This is particularly relevant in a transit-rich region such as Los Angeles with many alternatives available in close proximity. For example, we have evidence, from analyses done as part of a different[25] research project, that phase 1 of the new Exposition (Expo) [26] light rail line in Los Angeles that replaced existing bus service has drawn patrons from several competing bus lines.

[25] Metro-funded ADMS (Archived Data Management Systems) research project undertaken by the USC METRANS Transportation Center.
[26] Revenue service for the Expo Line Phase 1 started around June 2012.

Third, and as explained in Section 3.1, our research framework is limited due to unavailability of patronage data along transit routes/chains (linked trips). It is therefore possible that our estimate of the reliability effect is not exactly accurate. However, we provide preliminary empirical evidence of the significance of service reliability. Also, we could not measure many service quality attributes that contribute to the variation in patronage across lines, and across modes (bus vs. rail). Omitted variables include stop/station environment quality, vehicle comfort and cleanliness, etc. Therefore, our models are not fully specified.

Finally, lack of data on the extent of earliness and lateness limits interpretation of results. All we can say is that increasing frequency of arrivals within the -1.0 to +5.0 minute interval with respect to schedule will potentially contribute to greater use of a line.

7. Conclusion and policy implications

Our analysis of the Los Angeles Metro system provides first empirical evidence that transit service reliability determines patronage; transit mode choice and transit route selection is based, in part, on reliability. Our research suggests that improvements in service reliability can make transit more attractive, and prepare it for competing with alternate modes in the presence of latent transit travel demand. Reliability investments can therefore help increase service consumption relative to supply, and make transit lines and systems more productive.

This paper does not demonstrate that service coverage expansions and other qualitative improvements are ineffective means of promoting patronage. We simply argue that on-time performance is just another critical dimension of transit service that should not be undermined during operating existing systems and planning new projects.

Increasing line-level or system-wide reliability is complex. It must include strategies that are not directly within the realm of public transit policy or under control of transit managers. For instance, bus-only lanes and signal preemption systems are theoretically straightforward means of improving on-time performance. However, implementation requires coordinated efforts of many agencies across jurisdictions responsible for managing multi-modal urban transportation networks. Fortunately, there are other "internal" strategies too. For example, real-time rerouting of transit vehicles around non-recurrent congestion, and real-time information sharing via mobile devices can improve both system performance and users' perception of service quality. There is no doubt that advances in intelligent transportation infrastructure and information technology will help manage and operate transit systems more efficiently than ever before, and consequently help improve service reliability. Among other strategies, better driver training, efficient route planning, stop consolidation, and avoiding vehicle bunching can contribute to service reliability (see Perk et al., 2008; Sterman and Schofer, 1976; Abkowitz and Engelstein, 1983). Also, availability of extra drivers, better vehicle maintenance, and prompt system repair are important.

Our bottom-line is that as public transit agencies in Los Angeles and many other metropolitan regions in the US continue to invest for the future, improving service reliability should be considered as critical.

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