Making Headways: An Analysis of Smart Cards and Bus Dwell Time in Los Angeles

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ABSTRACT

This report provides an analysis of smart card fare payment systems and their relationship to dwell time of Los Angeles Metropolitan Transportation Authority (Metro) buses. First, the primary determinants of dwell time are discussed through a review of existing literature and research. Then, I use data collected from automatic passenger counter (APC) and automatic fare payment (AFC) systems to estimate a regression model of dwell time with Metro's smart card fare payment system relative to other factors. Variables such as passenger boarding and alighting, wheelchairs, bicycles, vehicle configuration, and service type are also examined and compared to the dependent variable.

An ordinary least squares regression model estimated with these variables explains 45 percent of the variance in dwell time. Statistically significant coefficients show that smart cards contribute roughly two seconds per person, while cash or other media contribute about four seconds. Using a smart card to purchase a pass or stored value at the farebox contributed about eight seconds. While smart cards contribute less to dwell time than other forms of fare payment, they are not the strongest determinant overall. An articulated bus, for example, reduces dwell time by three seconds on average, and as much as 13 seconds in crowded conditions; similarly, wheelchair boarding and alighting add as much as 35 seconds. These findings suggest that smart cards can be instrumental in managing delay at stops, but are best used with other strategies.

Keywords: Transit Data, Big Data, Public Transportation, Data Analysis

INTRODUCTION

Proponents of electronic ticketing systems claim that smart cards such as Metro's Transit Access Pass (TAP) can decrease the amount of time transit vehicles spend at stops while processing boarding passengers, or "dwell time." Because of many factors – an abundance of passengers, Americans with Disabilities Act (ADA) requirements, or congestion – dwell time can vary considerably. Long dwell times can degrade schedule adherence, cause delays, and cultivate a negative perception of transit as slow and unreliable. Long dwell times also contribute to longer runtimes, which increase the cost of service because more buses are required to maintain consistent headways. While a given amount of dwell time is accounted for in scheduling, transit agencies are very concerned with reducing the variance in dwell time to the extent possible because the marginal cost of extra transit service is very high, particularly during peak hours.

Although it is just one of the many aspects that determine the length of dwell times, electronic fare payment is thought to help schedule adherence by streamlining fare collection. In this way, TAP cards could possibly reduce the amount of time each person spends paying their fare. All things being equal, a passenger may save time by simply touching his or her TAP card to a validator rather than sliding dollar bills and coins into the fare box. Despite the fact that even the longest time spent paying fare may amount to a quarter of a minute, multiplying a few seconds of time savings per patron over hundreds of bus runs by thousands of stops serving tens of thousands of passengers could contribute a great deal to schedule adherence, service quality, and travel times.

The objective of this research is to examine the effect of TAP card usage on bus dwell times. I hypothesize that higher ratios of TAP cards to cash fare payments per stop will result in shorter dwell times overall because of the reduced fare processing times per person with TAP. My analysis relies on a number of tests conducted on automatically generated data, and indeed finds statistically significant reductions in bus dwell time associated with higher TAP card usage. Using linear regression analysis to statistically control for other factors known to influence dwell times, I find that fares paid with a TAP card contribute less to dwell time than other, non-TAP transactions, *ceteris paribus*.

However, the influence of TAP card usage on dwell times is not as strong as for other factors analyzed in my model. In addition, I observe that the effect of TAP card usage on dwell times appears to erode appreciably in crowded conditions. In other words, if reducing dwell times were the only, or even the primary, goal of implementing TAP cards – which is decidedly not the case – there are likely more cost-effective ways to reduce dwell times – such as all-door boarding at high-volume stops and stations.

CONTEXT AND PRIOR WORK

Researchers have identified a litany of factors that can influence the variability of dwell time, and as a result the policies, procedures, and even transit vehicles have changed over time to reduce delay at stops. Before the literature on the determinants of dwell time is examined, I first define what dwell time is and then place it conceptually in the context of bus transit route capacity. Next, I define the determinants of dwell time, and then explore relevant research findings for each.

Transit agency staff often regard dwell time as a factor of delay that is most within their influence, so there is a well-developed literature on the factors that most affect dwell time and dwell time variance. Accordingly, I draw on this work in developing my findings outlined later in the report, as well as in developing my research methodology. However, analysis using automatically generated data is relatively new, so I could find only a few articles that analyzed extremely large datasets on dwell times. Thus, beyond its immediate relevance for Metro, this research also seeks to fill a gap in the literature concerning the role of smart cards in dwell time variability; I do this by testing a process for combining two datasets that do not have a pre-defined relationship, which I explain further in the methodology section.

Definition of Dwell Time

The Transit Capacity and Quality of Service Manual (TCQM), published by the Transit Cooperative Research Program (TCRP) offers the definition of dwell time as "the amount of time a transit vehicle spends at stops and stations serving passenger movements" (1) as well as the time from the beginning of this sequence of movements to the end: bus arrives at stop, doors open, passengers embark/disembark, doors close, and bus departure (2).

According to the TCQM, dwell time is a function of passenger volume, fare payment method, vehicle type and size, and circulation of passengers within the vehicle (3). Within the realm of passenger activity, fare collection is a major determinant of dwell time (4). However, the role of smart cards is not mentioned explicitly and the strength of the relationship between their use and dwell times is not estimated.

While past dwell time studies were carried out through manual observation, (5) advances in automatic vehicle location (AVL) and automatic passenger counter (APC) technologies enable researchers to leverage vast amounts of data to analyze many thousands of dwell time observations, along with other variables, for more nuanced analyses.

Passenger Volumes and Load

Many researchers have proven the correlation between passenger volume and dwell time. Milkovits (6), Lin and Wilson (7), Rajbhandari, Chien, and Daniel (8), and Deuker, et al. (9), estimate a model for the dwell time of transit vehicles based on passenger activity. In addition to finding a positive correlation between passenger volumes and dwell times, all three found that that existing vehicle passenger load factors prior to arriving at the stop are correlated with longer than normal dwell times.

Service Type

Some research has shown that dwell times tend to differ based on whether the type of service was local (makes frequent stops serving only one or two passengers at each) or a limited-stop service (sometimes called "express" or "rapid" service, which makes fewer stops but serves more people at each, in order to move more quickly). Fernández, et al. (10) calculated a dwell time model based on observations of the bus transit network in Santiago, Chile. They found that trunk lines operating with high demand, low-floor vehicles, and less frequent stops, boarding time per person increases when there are more than 15 people in line. On feeder services, the boarding time is slower, and if there are many people, the boarding time slows even further. The differences between limited-stop express routes and local routes with many stops are accounted for in this research by examining the two different types of bus service separately.

Vehicle Configuration and Passenger Circulation

Configuration of the transit vehicle itself can allow for easier passenger movement in times of crowding thereby allowing patrons to board the bus more quickly. Daamen, et al. (11) and Fernández, et al. (12) conducted live experiments using a mock transit vehicle and platform. They found that dwell times associated with passenger crowding were correlated with door size and also whether or not the passenger had luggage. Fernández, et al. found that, in almost every case, wider doors had a significant effect on reducing boarding and alighting times; with wider doors, platform height had a very small effect on boarding and alighting times (13). Deuker, et al., also found that low-floor busses had shorter dwell times, *ceteris paribus* (14).

Aashtiani and Iravani (15) focused on how the layout of the transit vehicle could improve passenger circulation and reduce crowding on the vehicle. The models they developed successfully estimated bus dwell times by accounting for both the design of the bus and in-vehicle passenger congestion, supporting the notion that dwell times are affected by not only passenger movement, but also by existing passenger loads prior to the stop. Larger vehicles with more doors were also found to deal with passenger congestion more effectively.

Fare Payment Procedures

Generally, paying with cash is the slowest method of all fare payment procedures because of the time it takes to assemble the correct amount of money and then to insert it into the farebox (16). It is also one of the dwell time determinants that is most within control of a transit agency (17). Until recently, non-cash fare payments were either a proof-of-payment system wherein customers bought a fare before entering the bus, or “flash passes” that allowed a customer to board after the driver visually inspects the pass. Now, new technologies allow for smart cards that can store a variety of passes and cash value to pay for a trip. Theoretically, this could enable passengers to board the bus faster than by paying in cash. Research concerning the relationship between smart cards and dwell is relatively new because data has only recently become available. However, a small number of existing studies attempt to quantify it.

First, the TCQM reports that, based on manual observations, the average service time involving a smart card is 3.5 seconds, whereas paying cash for the fare is 4.0 seconds (18). A shorter processing time per passenger implies that the higher smart card usage would result in a shorter dwell time. Iseki et al. (19) undertook a meta-analysis of the cost-benefit reports from three transit agencies in the United States that are implementing smart card fare payment systems. The analysis was concerned with quantifying some of the often-reported but mostly unquantified benefits of smart cards, including decreased fare payment time. The authors found that fare-processing time was reported to be a definitive benefit of smart card systems, and in particular discovered that Metro experienced an improved average fare processing time of 2.27 seconds compared to 3.07 seconds for a non-smart card transaction (20).

Fernández, et al. found that fare payment methods had a significant effect on dwell times, but the effect was smaller than door size. On-board smart card payment reduced times by 10 to 35 percent while off-board pre-payment (proof-of-purchase) reduced boarding times by 25 to 45 percent (21). Milkovits (22) conducted a study to model the determinants of dwell time and their significance using automatically generated bus transit data. Among other factors, he modeled the role of smart cards specifically. His findings indicate that the time savings difference in using smart media fare cards over magnetic stripe cards is only significant when buses are not crowded due to standing passengers restricting prompt boarding.

To summarize, prior work has found that passenger volumes, service type, vehicle configuration, and fare payment procedures all have important roles in determining the length and variability of bus dwell time. The relative influence of smart cards, however, has not been investigated in much detail. Additionally, the use of automatically-generated transit data are just beginning to allow for rigorous statistical analyses with very large sample sizes. Drawing on the research literature to inform the selection of variables and methodology for analysis of large, computer generated data, I attempt in this analysis to fill the gap of knowledge regarding smart card systems and their effects on dwell time. My data pre-processing, variable construction, and calculations rely extensively on the prior work discussed in this section.

METHODOLOGY

To conduct this research I use transit data generated from on-board systems to estimate a regression of Metro bus dwell times, with the goal of determining the effect of smart card fare collection relative to other factors. By using ordinary least squares regression to statistically control for a wide array of factors thought to affect dwell times – rather than examining TAP card usage irrespective of these other factors – I am able to leverage massive volumes of available data to estimate the independent effect of TAP card usage on dwell times, and easily attain statistically significant findings.

The data provided by Metro are very rich, and allows for a range of controls to account for the many other factors that influence dwell time. The trade-off, however, for such a large sample size is a lack of fidelity associated with malfunctioning hardware. Accounting for this required numerous pre-processing steps. Along with a description of the data itself, this section provides the justification for route and sample size, exclusions, pre-processing, and variable selection.

Data Sources

Metro provided Universal Farebox System (UFS) and Automatic Passenger Counter (APC) data from March 3 to March 16, 2014. March was selected because of the relatively few holidays and special service days during that time. Because prior work suggests that limited-stop services have different dwell times than local services (23), two contrasting Metro bus lines were selected for analysis: a limited-service, low ridership neighborhood route (Local Route 120) and a high-volume, high frequency rapid route (Rapid Route 720).

The two primary sources of information are the Automatic Passenger Counter (APC) system and Unified Farebox System (UFS). The APC records the number of passengers who board and alight from the bus at a given stop and the number of passengers onboard the bus after it departs from a stop. The APC also contains information about the physical characteristics of the vehicle such as number of seats, direction of travel, and the geographic coordinates of the bus at each stop. The UFS records fare box transactions, including TAP card and cash payments. Additionally, bus operators use it to record some non-fare payment activity such as bicycle and wheelchair loadings. While the UFS automatically generates fare payment records when they are received, the operator is responsible for noting all other records in a timely fashion. However, as with any system dependent on human action, this does not always occur as it should. Finally, while cash payments are recognized by the system, it cannot determine which fare the cash was for until the operator classifies it. For example, if a passenger pays the Senior/Disabled fare of 75 cents, the UFS will not recognize it as such until the transaction is classified "S/D Fare" by the operator. Otherwise, it remains unclassified.

The TAP card data contain information about the type of fare media used and the status of the transaction, which could be either a "sale" or "use" depending on whether the passenger was purchasing a card with pass or fare while boarding or expending a fare already stored on the card. It is important to note that fare products such as day passes can be purchased from the fare box on a TAP card. It is possible, and perhaps likely, that such a transaction may take longer than simply using the TAP card. Fortunately, these transactions are recorded separately in the data.

Because the UFS and APC systems are not explicitly linked, there are significant obstacles to relating them. Without a shared key index, there is no direct way to associate a given APC record with a UFS record. Dwell time and fare payment information were thus joined on the basis of date and time, using vehicle identification number as a control to prevent the possibility of two records being matched temporally, but not geographically. If a fare record was generated between the dwell time of a given stop, and the vehicle ID number is a match, those records are related in my data.

The lack of direct connection also gives rise to the possibility that their clocks are not synchronized. While the APC derives the time from the global position system (GPS), the UFS is updated only when its data are downloaded at the bus facility, which is scheduled to happen nightly but may not always occur. Since the UFS clock is not updated throughout the day, it may slowly fall out of line with the APC. Adding further uncertainty is the fact that the computer that stores the UFS data and updates the clock may itself be incorrect. If the time is not consistent across the APC and UFS, then their data may be incorrectly associated by my methodology. A time differential could be calculated to account for this, however if the system clocks are unsynchronized it would be on a bus-by-bus and day-by-day basis. Systematic differentials for the entire sample would be impossible to estimate from manual observation because the data are just over a year old at the time of this writing.

Extending the time frame used for establishing a relationship between dwell time and fare payment could help to account for clock-related discrepancies. Also, UFS, wheelchair, or bicycle records may be created after the bus operator closes the doors, meaning that they are not clearly associated with a stop because the time stamp falls outside of the dwell time. Many UFS records rely on the operator to manually enter data, so this may occur if the operator closes the doors before all the passengers completed boarding; or if the operator tallies a bicycle before or after cycling the doors; or if the operator tallies a wheelchair before or after cycling the doors. In order to account these situations, a grace period of fifteen seconds after the door closed was added to each dwell time observation. Then, a fare box, bicycle, or wheelchair record that is created between the door opening time and the end of the grace period are related to that stop. An additional variable was created that counts the number of fare records (not including bicycles or wheelchairs) that occur between the door closing time and the grace period to account for the effect of passengers in the process of paying fare after the doors have closed.

Metro's Service Performance Analysis (SPA) group purged the data of most erroneous records before releasing it to me. This purge included consolidating instances of APC records where the doors cycled in rapid succession and removing records that were obviously created by malfunctioning hardware. I was not provided with the raw data, so it is not possible to determine how these changes may have affected the result of the analyses.

Finally, the APC dwell time calculation I use in this study is not consistent with the literature; in my data, dwell time is the difference between the doors fully opening and the doors fully closing, while the TCQM definition includes arrival and departure times. The Automatic Vehicle Location (AVL) coordinates embedded in the APC data are not precise enough to measure those movements. However, because this research is concerned with the effect that smart cards have on dwell time as it relates to passenger activity, and given that decelerating into and accelerating out of stop is not thought to be affected by smart card use, I find this discrepancy acceptable.

Exclusions

Dwell time records with a passenger service time below a half-second were excluded from my sample to account for malfunctioning APC units. To further account for malfunctioning equipment or misreported data, records of stops with dwell times of zero were also excluded. Often, these records had no indication of boarding or alighting passengers.

Sometimes, buses may wait with the door open at layover or terminal stops, leading to a longer dwell time not associated with passenger activity. Therefore any record generated at a known time point, layover, or terminal stop was deleted.

Remaining outliers were excluded by deleting records with a dwell time longer than 180 seconds (3 minutes). While occasionally very high numbers of passenger boardings could account for dwell times greater than three minutes, it is far more likely that such lengthy dwells are due to atypical circumstances, such as operator-passenger conflicts.

After excluding over 25,000 records, the sample size remains quite large with 540,407 fare payment records and 99,453 dwell time records across 342 operators and 187 vehicles.

ANALYSIS

Descriptive analysis of the variables reveals trends and establishes context of the transit operating environment. Here, I define the variables and explore their relationships to each other. Differences in means t-tests establish whether and to what extent the variables have a statistically significant relationship to dwell time. A multivariate ordinary least squares (OLS) linear regression model is then estimated to highlight the relative importance of a TAP card for dwell and passenger service time while controlling for other factors. The OLS regression is run for the whole sample and for a subset of the sample characterized by high passenger crowding. Table 1 below shows a summary of the variables considered in the regression and a short description of their origin.

TABLE 1 Variable Descriptions

Variable	Description
Dwell Time	*A dependent variable. Time between doors opening and doors closing.*
Passenger Service Time	*Time necessary for boarding and fare processing per person, calculated as dwell time divided by boarding passengers.*
Ons (no UFS)	*The number of boarding passengers when they are greater than the number of UFS transactions at each stop.*
Offs (Offs > Ons)	*The number of alighting passengers when they are greater than boarding passengers.*
TAP Fare	*The number of UFS transactions involving a TAP card for fare payment or pass use.*
Non-TAP Fare	*The number of UFS transactions not involving a TAP card.*
TAP (Sale of Stored Value or Pass)	*The number of UFS transactions involving a TAP card for purchase of stored fare value or pass.*
Fares in Grace Period	*Number of UFS transactions that occurred during the door grace period (15 seconds after closing).*
Wheelchairs	*Number of boarding or alighting wheelchairs per stop.*
Bikes	*Number of bicycles loaded or unloaded per stop.*
Dwell Load	*Number of people onboard when the bus arrives at a stop.*
Peak Hour	*A dummy variable that indicates if the bus stopped during rush hour. (1 = Yes / 0 = No)*
Night Time	*A dummy variable that indicates if the bus stopped at night. (1 = Yes / 0 = No)*

Articulated Bus	*A dummy variable that indicates if the bus is articulated or not. (1 = Yes / 0 = No)*
Service Type	*A dummy variable that indicates the service type – Rapid or Local. (1 = Rapid / 0 = Local)*
Abnormal Passenger	*A dummy variable associated to a passenger service time greater than 18 seconds, with only one boarding or alighting. (1 = Yes / 0 = No)*
Wide Doors	*A dummy variable that indicates whether the bus has wide doors (space for two people to alight simultaneously). (1 = Yes / 0 = No)*
Low Floor	*A dummy variable that indicates whether the bus is a low floor model or not. (1 = Yes / 0 = No)*

Passenger Activity

The length of dwell time is highly dependent on the volume and characteristic of passenger activity. Therefore, I create as many variables as possible to control for the variety of passengers and activities that occur at each stop.

Passenger Service Time

The time it takes for each passenger to board the bus and pay their fare, calculated by dividing dwell time by boarding passengers. Though this variable is not included in the regression because it is calculated from the dependent variable, it serves to highlight differences in the time taken per passenger and further illustrate a given variable's influence on dwell time.

Ons (no UFS)

Because boarding passengers and fare payment variables were found to be highly co-linear, this variable only counts boardings when they exceed the number of fare transactions per stop. Because APC units count boardings regardless of the door, this variable can control for fare evasion or other instances where a passenger does not interact with the UFS.

Offs (Offs > Ons)

Passengers alighting will not contribute to overall dwell time unless there are far more of them than boarding passengers. Therefore, alighting passengers are not included in the analysis except where the number of alighting passengers is greater than the number of boarding passengers. This is captured in the variable "Offs (Offs > Ons)."

Dwell Load

Passengers on a bus before it stops would affect dwell time by adding to the interior congestion that boarding passengers must wade through (24). Dwell Load is thus calculated by subtracting boarding passengers from the APC's load count. When the result of this calculation is a negative number, Dwell Load is zero.

Bikes and Wheelchairs

Because the data are manually tallied by Operators and thus of unknown integrity, I aggregated loading and unloading into one variable each for bicycles and wheelchairs.

Irregular Passenger Activity

The data may not always account for wheelchairs or other passengers – such as the elderly – who need extra time to board, pay, and sit down. An operator may wait for an elderly passenger before closing the doors and departing. I attempt to control for these situations by creating a dummy variable based on an abnormally long dwell time (greater than 18 seconds) with one boarding or alighting passenger.

Peak Hour and Night

These variables control for changes in people's behavior based on the time of day or peak hour service. Peak Hour and Night are two categorical binomial dummy variables that indicate whether or not the bus stopped during peak hour service or at night.

Fare Payment

TAP-Related fares are stored value cash or pass uses. Non-TAP Fares are cash fare payments or a visual inspection of a paper pass. It also includes tallies of insufficient fares or invalid transactions. These data are not excluded because they still represent a passenger interacting with the farebox in some way, thus contributing to dwell time. TAP-Sale of Pass are records of a rider purchasing a pass at the farebox.

Service Characteristics

Based on prior research suggesting that the type of service and vehicle configuration can also impact dwell times, I create dummy variables to describe vehicle and route information.

Bus Type: Low-Floor, Articulated, and Door Width

To control for the influence of vehicle configuration on dwell time, I created three dummy variables: low-floors, body type (articulated or standard), and door width. Sixty-foot articulated buses were 75% of the sample; 45' non-articulated, low-floor buses were 24% of the sample; 40' low-floor buses were one percent of the sample; and 40' high-floor buses were less than one percent of the sample.

Service Type

A dummy variable that controls for the differences in operating environment between the Rapid 720 and Local 120.

Variable Descriptive Statistics

After processing, the mean dwell time of both lines is 26.7 seconds per stop, and the mean passenger service time is 7.3 seconds per person (Table 2, below). Line 720 has consistently longer dwell time, passenger service time, boarding and alighting passengers, and crowding than line 120. This may be attributed to the 720's higher passenger volumes, as demonstrated through the original "On" and "Off" data which are included for reference in the table. High standard deviations demonstrate the extreme variability of passenger activities across both routes.

TABLE 2 Variable Descriptive Statistics

	Routes 720 and 120 (N = 99,453)					Route 720 (N = 74,723)					Route 120 (N = 24,730)				
	Mean	Median	Std. Dev.	Min.	Max.	Mean	Median	Std. Dev.	Min.	Max.	Mean	Median	Std. Dev.	Min.	Max.
Dwell Time	26.7	17	25.6	1	180	29.9	20	26.8	1	180	17.1	11	18.2	1	180
Passenger Service Time	7.3	5	11.1	0	180	7.4	4.8	11.1	0	180	6.9	5	11.1	0	179
Ons	3.4	2	4.8	0	52	4.2	2	5.3	0	52	1.2	1	1.7	0	31
Offs	3.6	2	4.8	0	65	4.4	3	5.2	0	65	1.3	1	1.7	0	31
Ons (no UFS)	0.7	0	1.6	0	44	0.9	0	1.8	0	44	0.4	0	0.9	0	30
Offs (Offs > Ons)	2.1	0	3.8	0	65	2.5	0	4.3	0	65	0.9	0	1.5	0	31
Dwell Load	22.9	18	19	0	107	26.1	22	20.3	0	107	13.2	12	8.8	0	71
TAP Fare	2.2	1	3.6	0	59	2.7	1	4	0	59	0.5	0	1	0	13
Non-TAP Fare	0.7	0	1.6	0	31	0.9	0	1.7	0	31	0.4	0	0.9	0	13
TAP (Sale of Value or Pass)	0	0	0.2	0	5	0	0	0.2	0	5	0	0	0.2	0	4
Wheelchairs	0	0	0.1	0	3	0	0	0.1	0	3	0	0	0.1	0	2
Bikes	0	0	0.1	0	3	0	0	0.1	0	3	0	0	0	0	2

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Relationship to Dependent Variable

Differences in means t-tests revealed statistically significant relationships between all of the categorical variables and dwell time, except for peak hour service. While irrespective of other factors this may be true, the regression analysis finds peak hour service to have a statistically significant coefficient.

Model Results, Interpretation, and Discussion

TABLE 3 Model Outputs

	Total Sample *Adjusted R-Square: .45 | N = 99,453*					**Congested Conditions** *Adjusted R-Square: .49 | N = 7,327*				
	B	Std. Error	Beta	T	p	B	Std. Error	Beta	t	p
(Constant)	11.5*	2.8		4.1	0	9.0*	3		3	0
Ons (no UFS)	3.8*	0	0.2	100.2	0	3.1*	0.1	0.3	32.2	0
Offs (Offs > Ons)	0.8*	0	0.1	46.4	0	1.0*	0.1	0.1	15.3	0
TAP Fare	2.7*	0	0.4	130.1	0	3.0*	0.1	0.5	48.2	0
Non-TAP Fare	4.6*	0	0.3	100.7	0	4.0*	0.2	0.3	26.3	0
TAP (Sale of SV or Pass)	9.0*	0.3	0.1	29	0	5.9*	1.3	0	4.5	0
Fares in Grace Period	-2.6*	0.1	-0.1	-41.3	0	-1.7*	0.2	-0.1	-6.9	0
Wheelchairs	36.9*	0.6	0.2	65.7	0	42.5*	2.2	0.2	19.2	0
Bikes	4.5*	0.7	0	6.9	0	1.8	2.1	0	0.9	0.4
Dwell Load	-0.01	0	0	-1.9	0.06	0.04	0	0	1.6	0.1
Peak Hour (1=Yes/0=No)	-1.0*	0.1	0	-7.9	0	0.3	0.4	0	0.6	0.6
Night Time (1=Yes/0=No)	-2.1*	0.1	0	-15.6	0	-2.1*	0.5	0	-4.4	0
Articulated Bus (1=Yes/0=No)	-3.3*	1.2	-0.1	-2.7	0	-11.9*	5	-0.1	-2.4	0
Service Type (1=Rapid/0=Local)	6.1*	1.2	0.1	5	0	14.1*	4.3	0.1	3.3	0
Wide Doors (1=Yes/0=No)	0.4	0.8	0	0.5	0.6	0.4	3.8	0	0.1	0.9
Low Floor (1=Yes/0=No)	1	2.9	0	0.3	0.7	-	-	-	-	-
Irregular Passenger (1=Yes/0=No)	24.0*	0.5	0.1	50.2	0	15.8*	2.7	0	5.8	0

** Significant at the .001 Confidence Level*

Table 3 above shows the output of the linear regression model in both an aggregated and congested form. A model using the entire sample can explain 45% of the variation in dwell time. Here, a TAP card used to pay for bus fare contributed fewer seconds per person to the overall dwell than their non-TAP counterparts. Increased volumes of passengers using TAP cards at a stop could then "reduce" dwell from the length caused by an equivalent number of non-TAP payments. Using a TAP card to purchase stored value or a multi-day pass at the farebox contributed the most time, perhaps because it is a relatively complex process. Also, the relationship may be exacerbated because the procedure is not widely published by Metro (25) so passengers or operators may be unfamiliar with the process.

Interestingly, fares paid during the grace period had a negative relationship to dwell time. My interpretation is that a fare paid during the grace period amounts to a "free" boarding in terms of dwell time; a fare payment recorded after the doors have closed by definition cannot count towards an increase in dwell time. While a bus operator who waits for everyone to pay and be seated would increase dwell time under the same circumstances, I do not believe this finding should serve as motivation for an operator to close the doors as quickly as possible. Driving while people are trying to pay for a fare could cause some passengers to lose their balance, and ensuring passenger safety should remain a priority for transit agencies.

Boarding passengers with no corresponding fare record contributed 3.8 seconds per person to dwell time. This finding is supported by literature that suggests an average boarding time of 4 seconds per passenger (26). When alighting passengers outnumbered their counterparts, each person contributed less than a second. This is expected considering that an alighting passenger does not need to interact with the farebox and wider rear doors can often accommodate two lines of people exiting at once.

Wheelchairs were associated with very large increases in dwell times (36.9 seconds), which is consistent with common operational knowledge. Lift operations require the Operator to hold the queue of boarding passengers so the ramp can open and allow the wheelchair passenger to enter or exit. If there is crowding on the bus, passengers must be moved away from the wheelchair area, causing further delay. Irregular passenger activity – when one person entering or exiting the bus took 18 seconds or more - contributed 24 seconds to dwell time.

Interestingly, bicycles were not associated with similarly long increases to dwell time. This may be because loading or unloading a bicycle can be done simultaneously with passenger boarding. Unless the bicycle loading process was longer than the passenger boarding time the overall effect would be similar to that of just another person.

Dwell times are shorter at night. Initially, I thought that a negative relationship would be due to the perception of safety – waiting for the bus at night may cause riders to step into the relative safety of the bus as fast as possible. However, a more realistic explanation may be that less people ride the bus at night, as sunset is well outside of peak hour service. However, this interpretation is problematic because volumes of boarding and alighting passengers are already controlled for in the regression.

Rapid service was associated with longer dwell times than local service. This is consistent with the literature and is explained by the less frequent but more crowded stops associated with limited service, despite the fact that reliability and speed between stops are improved. This relationship could be exaggerated to some degree because the 720 and 120 are so extremely contrasted in terms of ridership and crowding. A dataset that contains more Rapid routes may find that not all of them are as crowded as the 720, thus diminishing relationship relationship's strength.

All of the coefficients in the regression were statistically significant except for Wide Doors, Low Floor, and Dwell Load. These findings are contrary to those in prior work. For doors and floors, this may be explained by the fact that the bus types with these configurations are a miniscule portion of the sample. The small beta values associated with both variables support this interpretation. Further, in this small number of cases, these vehicles were likely to have been put into service atypically. For example, a non-articulated, low-floor, wide-door standard bus pressed into service on a Rapid line (usually served by articulated vehicles) might experience longer boarding and alighting times due to very high passenger loads in comparison with more typical operating conditions. Because the prior work indicates that both low floors and wide doors are associated with improved dwell times (27), I suspect that a sample with more variety of vehicle configurations would result in statistical significance for these floor and door variables.

An ordinary least squares regression model may not be the ideal model form to analyze dwell loads. For example, passenger congestion may influence dwell time only when the bus approaches seating capacity and people begin to stand. At that point, the crowding effect imposed by standing passengers upon boarding passengers would increase with each subsequent person. Thus, congestion may have an "increasingly increasing" exponential effect. Further iterations of this model should use a congestion variable similar to one developed by Milkovits, who calculated it as the square of the number of standees multiplied by the number of boarding passengers (28).

Crowding

While the definition of crowded conditions on a transit vehicle is not institutionally defined, I use the ratio of passengers on board to total seats ("Load Factor") as a scale. Based on Milkovits' methodology, passenger congestion becomes an issue when the number of people equals the number of seats, because not everyone will sit down given the opportunity (29). To see how congested conditions affect the model, I re-ran the regression after filtering the sample for records with a load factor of one or higher. The output of the model is displayed in **Error! Reference source not found.**.

With an adjusted r-square of 0.49, this model can explain 49 percent of the variance in dwell time. Similarly to the prior model, the impact of wide doors and dwell load were not found to be statistically significant. Low floor buses were automatically excluded from the model. Peak hour service also lost significance, as did the influence of bicycles.

With congestion, almost all of the variables contribute more time than in the prior model, including the TAP card. Notable exceptions include irregular passenger activity and articulated bus. An explanation for the former may be that there are less instances of such passengers in the highly constrained sample. Articulated buses reduce dwell time by almost 12 seconds in this model, whereas in the previous model the reduction was a more modest three seconds, highlighting these buses' ability to effectively deal with crush loads. This finding suggests that higher-capacity articulated buses are well-suited for managing dwell times given crowding.

Importantly, this model shows how on-board crowding can exacerbate dwell times. Variables which contribute to shorter dwells are less effective, while those that are associated with longer dwell times are magnified. From this, I infer that heightened crowding inhibits some of the benefits that the TAP card offers in terms of dwell time – however it doesn't totally eradicate them.

Research from prior work achieved higher explanatory power than these models, perhaps due to heightened specificity. For example, Milkovits estimated separate models for each door, on each bus, in crowded and open conditions (30). In my analysis, the model is generalized across all doors and bus types. Using one model to explain the variances across two very different routes and vehicle configurations may be responsible for a loss of explanatory power. A future analysis that includes all Metro bus routes and a more specified model may improve the model's power.

CONCLUSION

The goal of this research is to determine if TAP cards had a statistically significant impact on the dwell times of busses in Los Angeles, using automatically generated data provided by Metro. A review of prior work established the relationships between a variety of determinants and dwell time, including passenger volumes, service type, vehicle configuration, and fare payment procedures.

Pre-processing of the data focused on removing outliers. Despite these exclusions, variance of dwell time along predicting variables – particularly passenger crowding – was high. Numerous differences-in-means tests found that, individually, all but one of the variables had statistically significant differences in mean dwell time. A regression analysis then highlights the influence of each variable relative to each other.

The linear regression model suggests that, all things held constant, a person paying fare with a TAP card contributes less time to dwell than other methods of payment with statistical significance. While two seconds of dwell time reduction per boarding may not sound like much, consider this: If 100,000 current customers (or about 20% of current non-TAP paying customers) were to switch to TAP cards, Metro buses would spend about 56 fewer hours *per day* waiting at bus stops. Less time at stops means higher average bus speeds, and higher bus speeds means lower headways and faster travel times. Thus, the “two second solution” may be more significant for improving Metro transit operations than it might at first appear.

Importantly, however, the TAP card begins to contribute more – rather than less – time to delay at stops in crowded conditions, suggesting that the benefits of TAP vis-à-vis dwell time are diminished with high passenger volume. Considering that smart card fare payment systems are incredibly expensive to install and operate, it would behoove transit planners to evaluate them as a tool in the transit system design toolbox, and not the golden ticket.

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