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Empirical insights on improving bus reliability at a rural transit system

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ABSTRACT

Using a comprehensive data set, we investigate the impact of drivers, vehicles, trips, months, and days of the work week on deviation of actual run time from scheduled run time. Our results provide insights into what makes a bus service more reliable by analyzing the year-long data set from Butler Transit Authority, Pennsylvania, which is a rural system. The multiple regression methodology we employ reduces omitted variables bias so that each included explanatory variable's coefficient estimate is relatively free from bias compared to more simplistic econometric methods such as correlation or bivariate regression. We find that problem drivers, lunch hour and afternoon peak times, November, and Fridays, are the variables that reduce bus reliability the most. Our study speaks to the critical need for information-intensive design and delivery of reliable bus service. Analyses of such databases help the public, in general, and the transit authorities, in particular, in providing efficient and effective bus service systems.

Contribution/ Originality

Our multivariate data analysis provides valuable insights about individual driver performance, vehicle performance, at the trip level, for months of the year, and days of the work week. Information raises public expectations and hence increases the importance of bus dependability. Improvements can be made by adjusting schedules for specific problem times, days, and months, and by focusing on troublesome drivers and vehicles.

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1. INTRODUCTION

Intelligent transportation systems (ITS) help monitor performance indicators such as: on-time performance, run time variation, and headway maintenance (see, for example, Nakanishi 1997). ITS is now widely used (a) for scheduling with retrospective data and (b) for control during the trip. Published schedules do not permit estimation since there is no variation in them. Designing and delivering high quality bus service requires ITS (see, for example, Strathman *et al.* 2002; Bertini and El-Geneidy, 2003; Xuan *et al.*, 2011; Cats and Loutos, 2016; van Lierop and El-Geneidy 2017). Before ITS, researchers relied on manually collected data from passengers, drivers, and managers (see, for example, Jennings and Dickins, 1958).

In this paper, we use Butler Transit Authority data that contains electronic information on bus rides in Butler, Pennsylvania collected through ITS. Such a database is more accurate and unbiased than a survey of drivers/passengers/managers that relies on their recollection and opinion as to whether the bus is early/late or on time. We estimate a multiple regression model and suggest managerial guidelines to maximize on time performance. The multiple regression methodology we employ reduces omitted variables bias so that each included explanatory variable's coefficient estimate is relatively free from bias compared to more simplistic econometric methods such as correlation or bivariate regression.

A trip starts when the bus departs the station and ends when the bus returns to the station. In our data, we have one bus serving the route, therefore, the Transit Authority does not have the famous bus bunching or bus pairing problem, but it does have a schedule adherence problem that needs to be ameliorated. Thus, our data enables us a cleaner perspective on why a bus is not on time, when it is the only bus serving the route and therefore is free from transfer problems, congestion, and the competition from other buses that a city bus may have.

The remainder of the study has the following structure. The next section reviews the literature, Section 3 depicts the explanatory variables we analyze regarding what makes bus service more reliable, Section 4 describes the database on which we test these explanatory variables, Section 5 presents and discusses the results of our estimation, and Section 6 summarizes and concludes the paper.

2. LITERATURE REVIEW

A large amount of literature exists on transportation, in general, and on bus scheduling, in particular, since millions of passengers use public transportation every day. For example, in Pennsylvania, nearly ½ billion passengers rode fixed-route transits in fiscal year 2013-14 and that figure has increased from about 400 million since the 2006-07 fiscal year (Pennsylvania Transportation Performance Report, 2015). We only provide a brief overview of the literature on bus scheduling due to space and scope considerations.

Daganzo (1997) defines passenger transportation as a game where the transit authority chooses the system structure and passengers find their best routes and departure times. Recently, as a result of the advances in communication technology, bus transit managers have begun to adopt information technology that tracks bus locations from a central location in real time. See, for example, Dessouky *et al.* (2003). Such technology helps improve control strategies over those that depend solely on local information, e.g., time of arrival. Strathman *et al.* (2002) show that designing and delivering high quality transit service is an information intensive undertaking. El-Geneidy *et al.* (2011) show that schedule revisions are necessary to improve run time and schedule adherence. Passengers are concerned about the time they remain waiting once they are on the bus (Cats and Loutos, 2016). For example, annual hours of delay per commuter is between 39-52 hours according to the Pennsylvania Transportation Performance Report (2015).

Based on the literature we study the explanatory variables listed in section 3.

3. EXPLANATORY VARIABLES

We have explanatory variables regarding drivers, trips, vehicles, months, and days of the work week.

Drivers
The bus driver's skill, attention, and attitude are clearly a factor in schedule adherence. Driver experience measured in length of time is part of the model used by Strathman *et al.* (2002). Number of drivers for each route, not their identities, is part of the model by Bertini and El-Geneidy (2003).

Trips
Almost every study in the empirical literature controls for departure time of trips. On a weekday morning most people go straight to work while in the afternoon they may linger more, may be more distracted, and may make a few stops before going home. This makes afternoon traffic more congested than the morning traffic. For example, Nakanishi (1977); Bertini and El Geneidy (2003); and El Geneidy *et al.* (2011) test for am/pm peaks.

Vehicles
Hamdouni *et al.* (2007) control for vehicle types in their bus data for Canada. Although they do not test for the importance of each type of bus, their implicit assumption is that type of bus matters in schedule deviations.

Months
Since weather affects driving conditions, seasons can be important in any transportation study. Nakanishi (1997) controls for quarters for 2 years. We can examine our data at a finer level and control for months.

Days
Cats and Loutos (2016) predict schedule deviations by day of the week and find that on Monday and Tuesday buses are more dependable than other days we now turn to our data.

4. DATA

The data are from the 2013 Butler Transit Authority Route 1 trips, in Butler, Pennsylvania, for Monday through Friday. The service area is 25 square miles, the population is 31,084, and the total number of passengers is 218, 278. Figure 1 shows the Automatic Vehicular Location (AVL) data collection:

- The bus enters into a virtual trigger box
- A global positioning system (GPS) signal is sent giving:
    - Exact date and time
    - Stop location
    - Time spent in virtual box (dwell time)
- The data is then sent to the database via a cellular signal.

Figure 2 shows the route map. The route is a loop – it starts and ends at the same stop. We have 59,266 observations that correspond to bus travel on weekdays in Route 1 in 2013 with 12 drivers and 6 vehicles. The first trip is at 7:30 am and the last trip is at 8:45 pm, with 13 trips on a weekday.

According to the descriptive statistics exhibited in Table 1 we observe the following: *Seconds Late* is about 7.5 minutes, on average, which is quite long for passengers waiting at the bus stops and for passengers on board. A small percentage of the time (0.5%) buses leave earlier than scheduled, which may dismay the passengers who arrive at the bus stop on time. Late departures (more than 5 minutes) occur at 70% of the bus stops, which is quite large. (The transportation literature does not consider less than 5 minutes late as late. We concur and report the statistic as such.) Together, early and late departures from the stops comprise about 71% of the departures from bus stops. Figure 3 displays a histogram of *Seconds Late*.

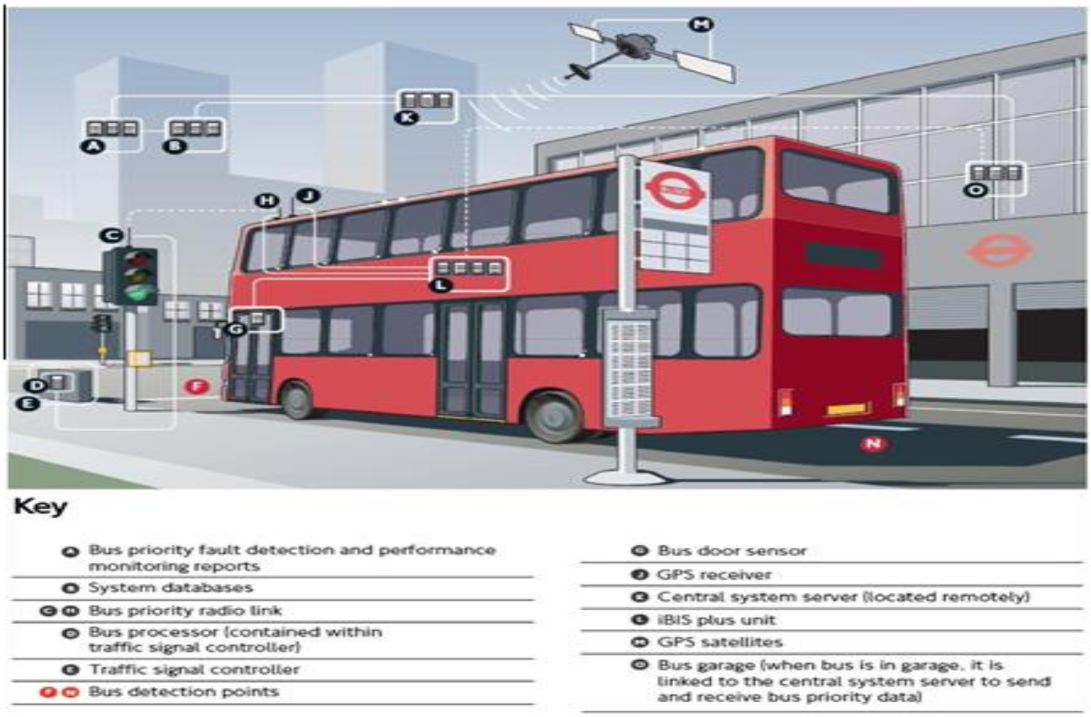

Figure 1: AVL Data collection

Note: The figure is from Hounsell *et al.* (2012)

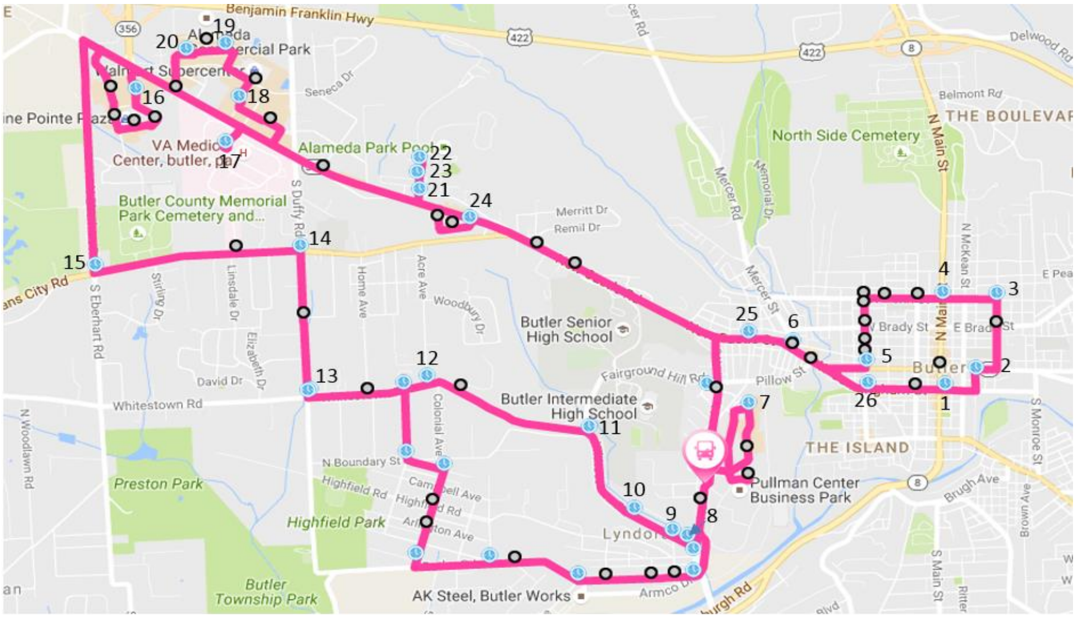

Figure 2: The transit system route map

Note: The map is from Butler Transit Authority website, www.butlertransitauthority.com

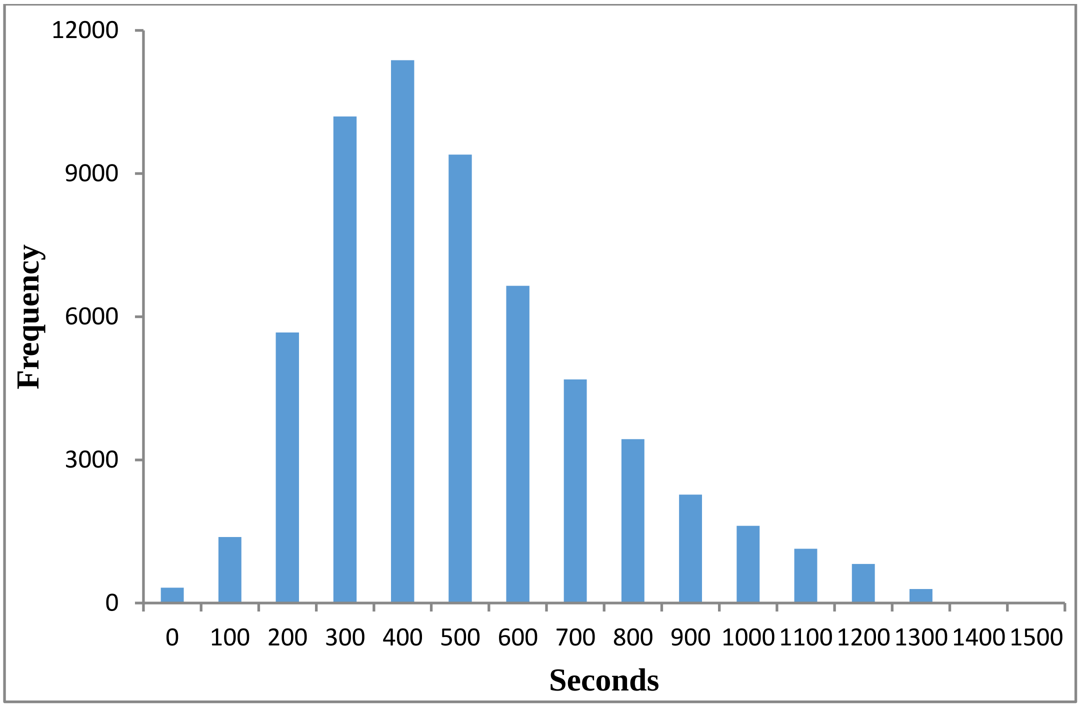

Figure 3: Histogram of seconds late

Scheduled and *Actual Run Times* differ: actual run times have a higher mean and higher variance than scheduled ones, which is not desirable to management or passengers. That is, buses are tardier and more volatile in their run times than the published schedules show.

Stop Dwell Time is about ½ minute, on average, which is reasonable, but may be as high as 11.5 minutes, which is too long for passengers on board and for passengers waiting at the next stop.

The remainder of Table 1 consists of descriptive statistics on binary variables (0, 1) for drivers, trips, vehicles, months, and days. Some drivers are employed more frequently than others, as seen in Table 1. We are informed by the Transit Authority that this is how they are assigned to this route. Trips are identified by their departure time from the first stop. Trips are more or less equal in terms of frequency, with evening trips being somewhat less frequent than morning or afternoon trips. Some vehicles are used more than others, perhaps they are newer and/or need less maintenance. Months and days are distributed more or less evenly throughout the year.

Table 1: Descriptive statistics

Variable List	Mean	Std. Dev.	Minimum	Maximum
Seconds Late	454.3235	248.2021	-1147	1488
Early Departure	0.0053	---	0	1
Late Departure (more than 5 minutes)	0.7035	---	0	1
Not on Time (combination of the above 2)	0.7088	---	0	1
Scheduled Run Time (seconds)*	3000.493	53.5806	2892	3028
Actual Run Time (seconds)*	3267.663	265.5087	2576	4125
Stop Dwell Time (seconds)	36.6647	27.5424	0	690
Drivers				
Driver B1	0.0059	---	0	1
Driver C1	0.0933	---	0	1
Driver G1	0.1164	---	0	1

Driver H1	0.0743	---	0	1
Driver I1	0.0127	---	0	1
Driver M1	0.1129	---	0	1
Driver P1	0.1825	---	0	1
Driver P2	0.0727	---	0	1
Driver S1	0.0386	---	0	1
Driver S2	0.1222	---	0	1
Driver T1	0.0453	---	0	1
Driver W1	0.123	---	0	1
Trips				
Trip 7:30am	0.0877	---	0	1
Trip 8:34am	0.0878	---	0	1
Trip 9:38am	0.0877	---	0	1
Trip 10:42 am	0.0864	---	0	1
Trip 11:46am	0.0825	---	0	1
Trip 12:54pm	0.0817	---	0	1
Trip 14:02pm	0.0777	---	0	1
Trip 15:10pm	0.0759	---	0	1
Trip 16:18pm	0.0729	---	0	1
Trip 17:30pm	0.0534	---	0	1
Trip 18:30pm	0.0736	---	0	1
Trip 19:30pm	0.0778	---	0	1
Trip 20:45pm	0.055	---	0	1
Vehicles				
Vehicle 841	0.0235	---	0	1
Vehicle 844	0.029	---	0	1
Vehicle 845	0.0247	---	0	1
Vehicle 846	0.0377	---	0	1
Vehicle 847	0.5165	---	0	1
Vehicle 848	0.3687	---	0	1
Months				
January	0.0857	---	0	1
February	0.0744	---	0	1
March	0.088	---	0	1
April	0.0905	---	0	1
May	0.0916	---	0	1
June	0.0817	---	0	1
July	0.0903	---	0	1
August	0.0822	---	0	1
September	0.0779	---	0	1
October	0.0919	---	0	1
November	0.0745	---	0	1
December	0.071	---	0	1
Days				
Monday	0.1949	---	0	1
Tuesday	0.219	---	0	1
Wednesday	0.2234	---	0	1
Thursday	0.2096	---	0	1
Friday	0.1531	---	0	1

Notes: Number of observations is 59,266 trips between bus stops. The statistics for run time variables (*) are calculated on 2487 round trips for the entire route.

Standard deviations of binary variables are not reported, by convention.

As a final descriptive statistic, we run a quadratic regression to see how tardiness varies during the entire trip. The dependent variable is *Seconds Late* and the independent variables are *Stop #* and (*Stop #*)^2. Ideally, the curve should be flat. The slope coefficients are 25.8023 and -0.6521, respectively, and both are statistically significant, with p-values <2e-16 ***. Figure 4 shows the predicted line. The results show an inverse-u shaped curve, which is mixed news for the Transit Authority. That is, although tardiness increases as the bus completes its round trip, it does not increase at an increasing rate.

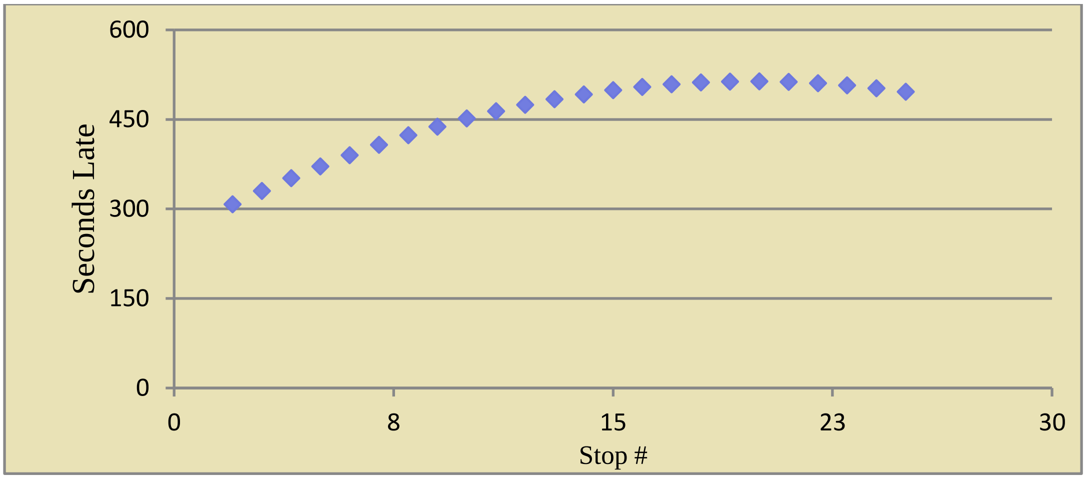

Figure 4: Seconds late prediction using quadratic regression

5. ESTIMATION

We now turn to our multivariate analysis which is more reliable than the methods above because it controls for omitted variables conditional on existing data. We use the R computer programming language to calibrate our model. Our dependent variable is run time deviation as measured by *{Actual Run Time - Scheduled Run Time}/ Scheduled Run Time*, a la Lin *et al.* (2008) and El-Geneidy *et al.* (2011). Table 2 displays the results. Almost all of our coefficients are statistically significant, owing to the relatively large sample size. Since all explanatory variables are dummy variables, the coefficient of an arbitrary variable in each category defaults to the intercept in the model.

In the literature, Strathman *et al.* (2002) do not find conclusive evidence on driver experience (measured in months of work). In our work, since we have data on the identities of drivers we can inform the managers of individual driver schedule adherence. Driver G1 is the worst and Driver T1 is the best performer in terms of adhering to the schedule over the entire trip.

Table 2: Multiple regression

Explanatory	Variable Coefficient	Std. Error	p-value
Intercept	0.0508	0.0100	3.81e-07 ***
Driver B1	0.0052	0.0181	0.7713
Driver C1	-0.0369	0.0079	2.83e-06 ***
Driver G1	0.0131	0.0047	0.0053 **
Driver H1	-0.0001	0.0061	0.9746
Driver I1	-0.0836	0.0116	7.44e-13 ***
Driver M1	-0.0104	0.0048	0.0285 *
Driver P1	-0.0333	0.0064	2.53e-07 ***
Driver P2	-0.0196	0.0075	0.0090 **
Driver S1	-0.0657	0.0074	< 2e-16 ***
Driver S2	-0.0124	0.0047	0.0080 **

Driver T1	-0.0852	0.0070	< 2e-16 ***
Trip 7:30	-0.0645	0.0089	6.39e-13 ***
Trip 8:34	-0.0393	0.0089	1.07e-05 ***
Trip 9:38	0.0071	0.0089	0.4233
Trip 10:42	0.0255	0.0090	0.0044 **
Trip 11:46	0.0703	0.0088	2.38e-15 ***
Trip 12:54	0.0634	0.0089	1.30e-12 ***
Trip 14:02	0.0600	0.0085	1.82e-12 ***
Trip 15:10	0.0849	0.0085	< 2e-16 ***
Trip 16:18	0.0583	0.0077	7.18e-14 ***
Trip 17:30	0.0122	0.0097	0.210872
Trip 18:30	-0.0326	0.0078	2.82e-05 ***
Trip 19:30	-0.0427	0.0077	2.95e-08 ***
Vehicle 841	0.0019	0.0081	0.810759
Vehicle 844	-0.0112	0.0077	0.147246
Vehicle 845	-0.0127	0.0081	0.114685
Vehicle 846	-0.0108	0.0066	0.103446
Vehicle 847	-0.0081	0.0027	0.002446 **
February	0.0132	0.0056	0.0188 *
March	0.0031	0.0055	0.5625
April	0.0219	0.0055	7.96e-05 ***
May	0.0339	0.0054	5.23e-10 ***
June	0.0454	0.0058	7.54e-15 ***
July	0.0420	0.0058	4.76e-13 ***
August	0.0514	0.0058	< 2e-16 ***
September	0.0570	0.0059	< 2e-16 ***
October	0.0488	0.0055	< 2e-16 ***
November	0.0586	0.0060	< 2e-16 ***
December	0.0515	0.0062	< 2e-16 ***
Tuesday	0.0098	0.0045	0.0264*
Wednesday	0.0109	0.0042	0.0087 **
Thursday	0.0151	0.0043	0.0003 ***
Friday	0.0288	0.0043	2.36e-11 ***

Dependent Variable = Actual Run Time - Scheduled Run Time/ Scheduled Run Time

Notes: Number of observations is 2,487 trips between bus stops. Adjusted R^2 = 0.4713, F-statistic = 51.37 with p-value 2.2e-16 ***

The first trip (Trip 7:30) is the best, that is, the deviation of actual run time from scheduled run time is the least at first. As the trip coefficients show, the misses in schedule rise as the day wears on. Trip 11:46 and Trip 15:10 are the worst perhaps speaking to lunch hour and afternoon rush hour traffic jams. However, drivers seem to catch up toward the end of the day as we start seeing negative and significant coefficients again. Our finding is consistent with the studies by Nakanishi (1997); Bertini and El Geneidy (2003); and El Geneidy *et al.* (2011).

Coefficients of vehicle IDs are more or less even, thus, any tardiness cannot be blamed on a specific member of the fleet, which is good news for the transit management.

November shows the largest deviation among months and Friday the largest among days. The November effect can be explained by several factors: For most people, an upcoming winter season is not a celebrated event. This adds to the negative emotions and, therefore, hostile driving on the road. In addition, according to the American Automobile Association (AAA, 2017), November is the month in which most fatalities occur on the road, due to adverse changes in the weather, the coming holiday season, and shortened daylight hours. Drivers have less time to get things done when the sun is gone and when the temperatures are lower, thus causing them to hazardously increase their speed and be more careless toward road rules. (In addition, in Butler County this is the heaviest month for deer to mate and migrate, and is the month when deer hunting begins. Therefore, deer are active and so are hunters, adversely affecting traffic since deer are more prone to jumping in traffic in order to, understandably, escape from gunshots.) All of these factors cause increased distraction, higher speed, and negative emotions, that contribute to delays on the road at best and accidents at worst.

The Friday effect is explained by AAA statistics that deem Friday as the day with the most accidents since drivers are distracted and unnecessarily hasten, in order to rush to their celebratory events. The name of the TGIF restaurant chain and the acronym TGI5 both verify the attitude of most people who cannot wait for work to be over. Our finding is consistent with Cats and Loutos (2016).

Figure 5 shows selected predictions from our model. Accordingly, Friday afternoon is the worst, followed by Friday noon, November, and September in terms of adhering to the published schedule.

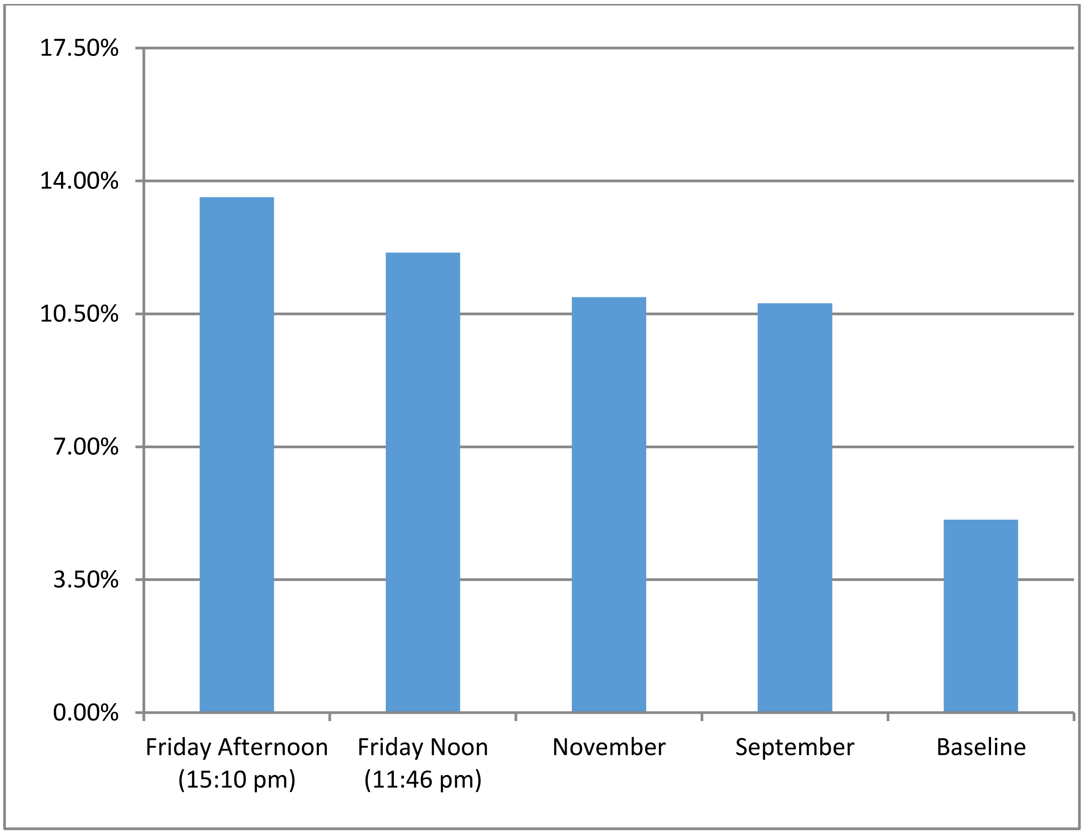

Figure 5: Predicted deviations from schedule using our model

6. CONCLUSION

We employ a multivariate estimation method, specifically, multiple regression, that enables us to simultaneously control for the 44 explanatory variables in the rich database we have from Butler Transit Authority, Pennsylvania. The method we utilize is more powerful and reliable than simpler econometric methods such as correlation or bivariate regression that only look at 2 variables at a time: dependent variable and an explanatory variable. The methodology we employ reduces omitted variables bias. It assigns cleaner estimates of coefficients for each explanatory variable because it controls for the effects of the remaining explanatory variables.

Based on our empirical analysis of the Butler Transit database collected through ITS, we suggest the following in order to improve bus dependability:

(1) Impose a financial penalty on a driver if s/he exceeds the threshold on not being on time, as is done in large cities, e.g., London UK.
(2) Educate passengers about problem trips such as lunch hour and afternoon peak, November, and Fridays. They should expect delays or avoid travel unless necessary during these times. Likewise, educate drivers about problem trips.
(3) Although vehicles do not seem to differ in our data, keep up the maintenance of vehicles to avoid unexpected delays and to save costs.
(4) Put quick response (QR) codes on posters at bus stops (a relatively inexpensive solution) a la Gammer *et al.* (2014). A QR code is a two-dimensional matrix that can be converted to information via smartphones with built-in cameras. QR codes enable access to a organization's website and numerous types of information for marketing the organization's products. See, for example, Gonul *et al.* (2016). A QR code shows, where the bus is, when scanned from a poster at a bus stop. A disadvantage may be that the poster can be damaged and therefore, has to be checked at regular intervals by the transit authority.
(5) Enact 511 for traffic and traveler information (Pennsylvania Transportation Performance Report, 2015). In fact, Butler Transit Authority recently implemented one to find out about bus availability (https://butlerivl.availtec.com/) for both desktops and mobile phones. Other mobile applications can be released to provide traffic flow maps and safety information for users.
(6) Adopt holding at median travel times at problem stops where the schedule needs the most adjustment. (See, for example, Xuan *et al.*, 2011). However, holding delays onboard passengers, potentially pollutes the environment, and wastes resources since the bus is idling.
(7) If scheduling is too much to handle at a local level, adopt regional transit systems to streamline administration, consolidate costs, and management of information (Pennsylvania Transportation Performance Report, 2015).

No study is without limitations. We do not investigate the adherence problem at the bus stop level, although for passengers, specific bus stops may have their own importance. Instead, we study the total run time at trip level to derive guidelines in the management of buses. In addition, our data is from a rural transit authority and hence is free from connection and congestion problems that a city bus may suffer from.

We find that information is crucial in providing reliable bus service. Our data analysis provides valuable insights about individual driver performance, vehicle performance, at the trip level, for months of the year, and days of the work week. Information raises public expectations and hence increases the importance of bus dependability. Improvements can be made by adjusting schedules for problem times, days, and months. Systematic failures in schedule adherence, such as the ones due to particular drivers or vehicles should be revoked, to the extent possible.

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