ARTICLE IN PRESS

Research in Transportation Economics xxx (2016) 1–8

Contents lists available at ScienceDirect

Research in Transportation Economics

journal homepage: www.elsevier.com/locate/retrec

Decreasing fare evasion without fines? A microeconomic analysis

Pablo Guarda [a, b, *], Patricia Galilea [a, b], Susan Handy [c], Juan Carlos Muñoz [a, b], Juan de Dios Ortúzar [a, b]

[a] Centre for Sustainable Urban Development (CEDEUS), Los Navegantes 1963, Providencia, Santiago, Chile
[b] Department of Transport Engineering and Logistics, Pontificia Universidad Católica de Chile, Vicuña Mackenna 4860, Macul, Santiago 7820436, Chile
[c] Institute of Transportation Studies, University of California at Davis, 1 Shields Avenue, Davis, CA 95616, USA

ARTICLE INFO

Article history:
Received 29 October 2015
Received in revised form
31 May 2016
Accepted 13 June 2016
Available online xxx

JEL classification:
C1
C5
R4

Keywords:
Fare evasion
Count regression models
Transantiago
Cost-benefit analysis

ABSTRACT

Fare evasion is a problem in many public transport systems around the world. Policies to reduce this problem are generally aimed at improving control systems and increasing fines for offenders. In this paper, we attempt to identify the joint impact of different variables explaining fare evasion using an econometric study. The variables found to be statistically significant are the level of inspection, the proximity to a Metro or intermodal station, the bus occupancy level, the period of the day, the geographic location and number of passengers boarding and alighting at each bus stop, among others. We propose a novel approach to perform cost-benefit evaluation in order to help authorities increase the cost-effectiveness of ticket inspection strategies on a given time horizon. We obtain new evidence that indicates that inspection strategies can be cost-effective even when evaders are not given a fine.

1. Introduction

Fare evasion is a problem in many public transport (PT) systems around the world. A survey from the *International Association of Public Transport* found that fare evasion averaged 4.2% across their sample of (primarily) bus services in 31 systems from 18 countries (Bonfanti & Wagenknecht, 2010). Fare evasion studies tend to view passengers as rational actors who maximize utility by trading-off the costs of buying a ticket with the costs of being caught without one (Boyd, Martini, Rickard, & Russell, 1989; Kooreman, 1993). In addition, studies have normally focused on the design of punishment strategies to tackle fare evasion (Killias, Scheidegger, & Nordenson, 2009; Lee, 2011). This, rather simplistic, view does not consider the different social and contextual aspects in which fare evasion takes place. Fare evasion levels are the product of a combination of factors including the level of income, the perception of the service, cultural components, level of enforcement and the operating characteristics of the public transport system, among others (Guarda, Galilea, Paget-Seekins, & Ortúzar, 2015).

Although governments have implemented different strategies to deal with this problem, both in Metro and bus systems, in many cases they have obtained unsatisfactory results (Boyd et al., 1989). Public policies usually focus on enforcement and punishment, combining infrastructure and ticket inspectors at strategic points (e.g. bus stops, Metro stations). In Metro systems, electronic tolls are usually implemented to reduce the ticket-issuing and inspection costs, while bus rapid transit (BRT) systems, for example, implement off-board stations managed by ticketing inspectors, allowing control of payment before passengers board buses.

The main objective of our study is to specify a cost-benefit methodology to help authorities determine the optimal budget distribution for the ticket inspection strategy analysed, given a set of bus stops and bus routes, to tackle fare evasion in a given time horizon. In the data we used for our analysis, inspectors located at bus stops could only remind passengers to pay the bus fare when boarding the bus. The role of ticket inspectors is to monitor payment of the bus fare, but they cannot fine evaders. To perform the cost-benefit analysis we formulated a microeconomic model that requires field data about fare evasion. Although some parameters of

* Corresponding author. Centre for Sustainable Urban Development (CEDEUS), Los Navegantes 1963, Providencia, Santiago, Chile. Fax: +56 (2) 2354 0281.
E-mail address: paguarda@uc.cl (P. Guarda).

http://dx.doi.org/10.1016/j.retrec.2016.06.001
0739-8859/

the model may change depending on the local context of the public transport system, the model can be adapted for application in almost any context as long as the required data is available.

The rest of the paper is organized as follows. Section 2 presents the framework to implement our methodology in practice. In Section 3 we discuss the main results so far and in Section 4 we present the conclusions and suggest further research.

2. Methodology

Some bus operating companies allocate ticket inspectors to those bus stops and bus routes (and time periods) where the highest level of fare evasion is observed. However, this criterion is not necessarily optimal since there are a number of variables that define the cost-effectiveness of ticket inspection strategies, such as: passengers' socio demographic characteristics, the capacity of inspectors to monitor high flows of passengers boarding and alighting buses, among others. We propose a simple framework with four steps to guide the evaluation and implementation of ticket inspection strategies to tackle fare evasion. First, we describe the data collection process used currently by public transit agencies in Chile (Step 1). Second, we explain how to use this data to estimate count regression models and predict changes in fare evasion on bus stops (Step 2). Third, we describe a heuristic to allocate ticket inspectors depending on both the current level of fare evasion at bus stops and the impact of inspection on fare evasion rates (Step 3). Fourth, we formulate mathematical equations to estimate the reduction in fare evasion due to the implementation of ticket inspection, given a certain budget and a time horizon (Step 4).

2.1. Step 1: Data collection

The Enforcement Commission of the Chilean Transport Ministry (MTT) and some private bus operators in Transantiago collect data about evasion for a sample of bus routes every month using plain-clothes observers (without an enforcement capacity). Once the sample of bus routes is selected, a sample of runs (bus trips) for each bus route is chosen to cover different time periods of the day and both directions of the bus routes. To collect data in the field, plain clothes observers are stationed inside the sampled buses next to each door and take notes (anonymously) about the number of people evading,[1] boarding and alighting at each bus stop by each door of the bus, as well as other conditions such as bus occupancy. To gather data for each door and all bus stops served by the bus route, the observers are distributed in groups that begin collecting data from the first to the last stop of the bus route. The size of each group depends on the number of doors of the vehicles operating the set of routes measured.

2.2. Step 2: Regression model estimation

Guarda et al. (2015) estimated regression models to explain fare evasion using a dataset collected by the Enforcement Commission of the Chilean Transport Ministry (MTT) during October 2012. They concluded that the Negative Binomial Regression (NB2 specification) was an appropriate methodology for modelling fare evasion rates. To use the information available in the least aggregate way possible, they defined the dependent variable as the amount of evasion at a given door and bus stop registered by a plain-clothes observer. According to this model specification, the number of people boarding and alighting at each door at all bus stops served by the bus route must be known to predict changes in fare evasion at each bus stop, since these are explanatory variables of the regression model. For our analysis, we will measure the effect of ticket inspectors located at bus stops, so we model fare evasion at the bus stops accordingly.

Therefore, we redefined the level of aggregation of the dependent and the explanatory variables. The dependent variable was defined as the amount of evasion measured at a given bus stop during a particular time of the day. Then, using the link function of the Negative Binomial regression model (1), the expected fare evasion count (E) is given by the following equation:

$$\log(\mathrm{E}) = \gamma \log(\mathrm{B}) + \sum_{k=0}^{K} \beta_k x_k \tag{1}$$

where x_k are a set of explanatory variables, β_k the estimated parameters for each x_k, B the number of boardings at a bus stop (*exposure variable*) and γ a parameter to be estimated. In Section 3.3, we describe all the explanatory variables included in the regression model specification.

2.3. Step 3: Allocation of ticket inspectors

Rather than formulating a formal optimization model, we used a heuristic to determine the set of bus stops, period of the day and bus routes where it would be more cost-effective to allocate ticket inspectors.[2] First, we calculated the number of inspectors ($I_{s,r}$) required to satisfy the demand of passengers at bus stop *s* using bus route *r*. As shown in (2), the number of ticket inspectors depends on the number of passengers boarding ($B_{s,r}$) at bus stop *s* during a certain time window and the capacity of each inspector (μ), that is, the maximum number of passengers that an inspector can control per unit of time (the brackets in the expression represent the ceiling function).

$$I_{s,r} = \left\lceil \frac{B_{s,r}}{\mu} \right\rceil \tag{2}$$

Secondly, a productivity index is calculated for each bus stop *s* served by route *r* ($\eta_{s,r}$), as the ratio between the estimated reduction in the number of fare evaders due to allocating inspectors and the number of ticket inspectors that the bus stop would require (3). As shown in (4), the expected reduction in the number of fare evaders per hour[3] ($\Delta E_{s,r}$) is a function of the estimated parameter for the explanatory variable capturing the effect of ticket inspections (β_o) in the regression model (Step 2) and the current level of fare evasion at the bus stop ($e_{s,r}$).

$$\eta_{s,r} = \frac{\Delta E_{s,r}}{I_{s,r}} \tag{3}$$

$$\Delta E_{s,r} = B_{s,r} e_{s,r} (1 - \exp(\beta_o)) \tag{4}$$

Thirdly, the overall amount of time for allocating inspectors (T) is distributed among the bus stops served by all bus routes (5). Then, the heuristic must satisfy the following budget constraint:

[1] They must register the number of evasions without being noticed by the passengers.

[2] Ticket inspectors wear a special uniform and are located at bus stops; they can only remind boarding passengers to pay their fares.

[3] In count regression models, the percentage change (PC) indicators are a simple way to study the impact in the dependent variable of changes in the explanatory variables. For both linear and categorical explanatory variables, PC is equal to $(\exp(\beta_k) - 1)$ and represents the percentage change in the number of counts for a unit change in a given independent variable (Guarda et al., 2015).

Please cite this article in press as: Guarda, P., et al., Decreasing fare evasion without fines? A microeconomic analysis, *Research in Transportation Economics* (2016), http://dx.doi.org/10.1016/j.retrec.2016.06.001