FARE EVASION IN PUBLIC TRANSPORT: A TIME SERIES APPROACH

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ABSTRACT

An econometric model is presented that identifies the main variables explaining evasion of fare payment on a public transport system. The model uses a cointegration approach. The model parameters are estimated using data from the Santiago (Chile) bus system, where evasion has been measured at approximately 28%. The main results of the model are that (i) a 10% increase in the fare raises evasion by 2 percentage points, and (ii) a 10% increase in inspections lowers evasion by 0.8 percentage points. An increase in unemployment, the third explanatory variable in the model, tends to induce a decrease in evasion, and vice versa. This counterintuitive finding may be explained by the fact that those most vulnerable to job loss, and more likely to evade than the average user due to economic necessity, tend to reduce their use of the bus system when unemployment rises and increase it when unemployment falls.

Our results suggest a revision of the evasion control policy in Santiago to improve its effectiveness, and to link inspection efforts to fare increases or to decreases in unemployment.

Keywords: fare evasion, public transport, cointegration, unemployment, fare inspection, Transantiago.

1. INTRODUCTION

Evasion of fare payment on public transport is a major problem for many bus and tram systems around the world that have not implemented an effective method of enforcement. As well as the ethical issues it raises, evasion can, if unchecked, become a major contributor to an operating deficit. In the case of Transantiago, the operator of an integrated transit system in Santiago, Chile, evasion is particularly common on the buses, where it has risen to about 28%, or more than one in four users. This is in stark contrast with the system's Metro network, where non-payment is no more than 0.2%.

Existing works on the phenomenon have focussed on the effectiveness of countermeasures in various specific contexts. To our knowledge, no previous publications have attempted to formally model the impact of potentially relevant factors on evasion. With the intention of filling this gap, the present study develops an econometric model that attempts to explain the long-term aggregate relationship between fare evasion and a set of variables that includes the amount of the fare, fare enforcement and unemployment. Changes in these variables as well as their absolute levels were considered. The data sets used to estimate the model are time series and as such, they may be non-stationary in the sample. This means the series must be checked for cointegration to ensure the regression estimates are not spurious.

The explained variable in the proposed formulation is monthly evasion (i.e., the percentage of users per month who evade fare payment) while the precise explanatory variables are the logarithm of the fare, the logarithm of the number of fare payment inspections (as a measure of fare enforcement), and the corresponding monthly unemployment rate in percentage terms. The errors are modelled as an autoregressive-moving average process (ARMA). The variable parameters are estimated by maximum likelihood using heteroscedasticity-robust variance-covariance matrices.

The main results of our model, estimated using data from the Transantiago bus system, indicate that an increase in bus fares leads to an increase in evasion while an increase in enforcement generates a slight decrease. A positive relationship was also found between evasion and unemployment, suggesting that those most vulnerable to job loss, and more likely to evade than the average user due to economic necessity, tend to reduce their use of the bus system when unemployment rises and increase it when unemployment falls. These specific findings and the proposed analysis of the determinants of evasion generally should be useful in helping transport system authorities to design better mechanisms for dealing with the public transit evasion problem.

The remainder of this article is organized in three sections. Section 2 reviews the literature on fare evasion in public transport; Section 3 describes the data, introduces the proposed models and presents the estimates generated; and Section 4 sets out our conclusions and their implications for public transport operation and subsidy policies.

2. SURVEY OF THE LITERATURE

Considering its importance for public transport finance and policy, fare evasion has received relatively little attention in the literature. The magnitude of the problem is reflected in the evasion rates for a number of transit systems around the world set forth in Table 1. As can be seen, with the exception of Reggio Emilia in northern Italy, the incidence of evasion in Europe is lower than that reported by Latin American cities. Santiago, Chile, the case study for the present article, has the dubious honour of topping the list with an evasion rate of 27.6%.

Table 1
Estimated Public Transport Fare Evasion Rate (*)

City	Rate	Year
Melbourne	5.0%	2015
Seattle	4.8%	2010
London	1.3%	2013
Vancouver	2.5%	2007
Sidney	2.3%	2006
Vienna	3.0%	2010
Cologne	4.7%	2012
Berlin	4.0%	2012
Bonn	3.9%	2012
Hamburg	3.5%	2012
Munich	3.0%	2012
Auckland	6.4%	2013
San Francisco	8.0%	2014
Reggio Emilia	43.0%	2012
Lima	10.0%	2016
Buenos Aires	12.0%	2016
Bogotá	15.0%	2016
Santiago	27.6%	2016

(*): Compiled from various publications; see Appendix for source details.

Much of the published research on evasion attempts to elucidate the reasons behind it, focussing on different attributes of both the evaders and the transit systems where the problem is particularly acute. Often cited are certain aspects of individual and social behaviour that might lead to evasion. The ultimate causes seem to lie in multiple factors such as passenger income, perceptions of service quality, fare payment methods and the behaviour of other passengers (Reddy et al., 2011; Bucciol et al., 2013).

Smith and Clarke (2000) note that fare evasion has legal repercussions much like other crimes or acts of dishonesty committed on public transport that may target other passengers, employees or the system itself. A recent paper by Guarda et al. (2016) uses a disaggregated negative binomial count regression model with cross-sectional data to identify operating factors in the Santiago, Chile bus system that impact non-payment of fares. The authors found that evasion increases with the number of passengers (level of occupancy), the number of passengers boarding/alighting at a given door and wait times at bus stops.

Delbosc and Currie (2016) conduct a quantitative analysis based on a survey of 1,561 residents of Melbourne, Australia, to characterize different types or clusters of evaders. They identify three categories: accidental (e.g., users who meant to pay but the ticket/validation machines were not working), unintentional (e.g., users who meant to validate but were in a hurry or forgot) and deliberate (e.g., users who decided not to pay because they were only going a short distance). The authors also briefly discuss the impact on evasion of different measures that have been adopted to combat it.

Polinsky and Shavell (1979), Boyd et al. (1989) and Kooreman (1993) propose theoretical approaches based on microeconomic modelling, assuming that evaders are rational actors who consider only the cost of the fares and the likelihood of being caught. The models take no account of the social context in which evasion occurs or of non-monetary penalties such as social sanctions (e.g., publishing the names of evaders).

Departing somewhat from the focus of the present article, Barabino et al. (2013) considers the issue of efficiency in fare inspection, examining factors such as the proportion of riders checked, the amount of evasion and transit system operator earnings. They find that the level of fines for evasion and the way they are collected both influence the cost-effectiveness of inspection efforts. According to Clarke et al. (2010), however, it is not clear what would be the optimal balance between the level of inspection and the size of the fine to reduce evasion to a minimum, or what might be the minimum achievable evasion level.

In a similar vein, Killias et al. (2009) report that the majority of public transport systems base their anti-evasion strategies on ticket inspection and fines for evaders. Bonfanti and Wagenknecht (2010) recommend that transit operators provide the requisite working conditions so that system staff can act as inspectors, though this role may be rejected at the political level or by the employees themselves. Gino et al. (2009) describes the influence of group dynamics, emotions and situational context in an attempt to better understand fare evasion as one type of unethical behaviour.

Regarding determinants of public transport demand, Paulley et al. (2006) offer a review of how fares, quality of service, income and car ownership affect the demand for public transport. In the same line, Cordera et al. (2015) study the demand for public transport during the economic cycle in the city of Santander, Spain. They find that recessionary periods with higher unemployment and lower income increase the demand for public transport.

Barabino et al. (2015) investigates evasion in Italy, where interest in the issue is growing due to the role it plays in transit operators' financial losses, social inequities and increasing levels of violence towards system personnel and other riders. Another recent paper, by Tirachini and Quiroz (2016), surveys the literature on the causes of evasion and makes a series of recommendations and suggestions for reducing it.

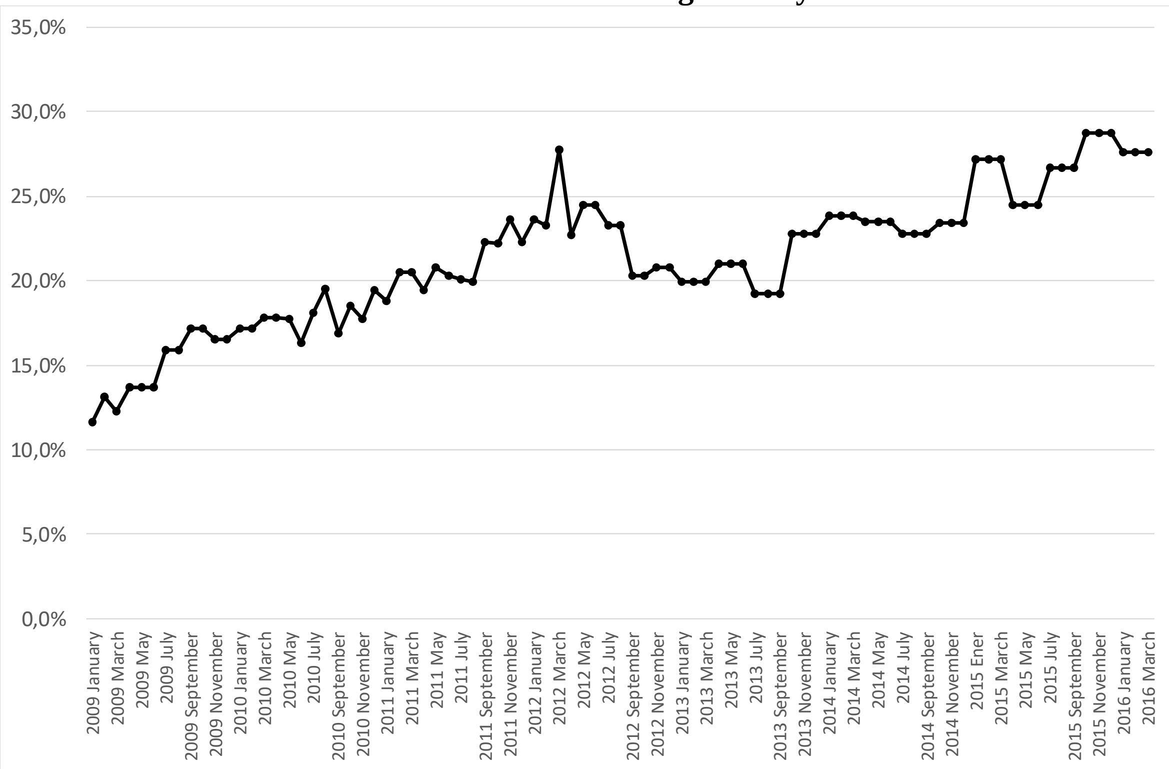
3. DATA, MODEL AND RESULTS

3.1 Data sets

The Transantiago system has been subject to constant scrutiny by Chile's political class and the general public ever since it was inaugurated in 2007 due to a number of costly errors in its original design. One of these errors was the assumption that the system could run without government subsidies (Muñoz and De Grange, 2010). Currently, Transantiago receives a subsidy that amounts to about 40% of its long-term operating expense and also covers part of the cost of infrastructure for new Metro lines and the entire capital and operating costs of bus garages.

In reaction to political pressures, the granting of these resources has been conditioned on promises of greater transparency, resulting, among other things, in the regular release of estimates of fare evasion on the buses. Figures are available on a monthly basis for the period from May 2007 to December 2012 and quarterly since 2013. These figures constitute the data set used for the explained variable in our proposed model.

Figure 1
Fare Evasion on Transantiago Bus System



The Ministry of Transport is responsible for measuring the fare evasion rates through its Inspection Unit (Unidad de Fiscalización). Fare evasion is estimated by sampling regular daytime services. The data are collected by incognito enumerators, so as not to induce changes in the behavior of evaders.

Data were also gathered for the three explanatory variables of an economic nature that could conceivably influence evasion. The first of these was the fare level. Increases in fares have always been controversial and are politically costly for the government of the day. It is reasonable to assume that fare hikes act as a disincentive for riders to pay for using the system, especially when inspection capacity is low.

The second variable for which data were collected was the level of employment in the Santiago region. This indicator is published by the National Institute of Statistics (Spanish initials: INE) as a three-month moving average. For our purposes the central value of the average was considered to be the most appropriate estimate.

The third variable for which we constructed a data set was the number of fare inspections carried out each month on the bus system. An inspection program run by the transport authority has published figures on the number of inspections since August 2008. Measurement of evasion and inspections are carried out by different agents.

Based on these three explanatory variables, multiple specifications of the proposed model can be constructed incorporating various different lags or time differentials. A fourth variable, the public's evaluation of the system as measured by a monthly survey, was also tested but found not to be statistically significant in any of the model specifications and thus was dropped from the analysis. Another relevant variable that we could have included is the level of fines, but fines have remained unchanged during the sample period (1.5 Chilean monthly tax units, or approximately US$ 105).

The data actually used for estimating our proposed model consisted of monthly figures from 2009, the year the Transantiago bus system stabilized and subsidies began, through February 2016. For the period in which the only published evasion data are quarterly (since 2013), the quarterly figure is used for all three corresponding months.

The basic descriptive statistics of the data sets and the number of observations are shown in Table 2.

Table 2
Descriptive Statistics (N = 86)

Variable	Mean	Std Dev	Min	Max
Evasion (%)	21.19	3.99	11.6	28.7
No. of fare inspections	101,207.9	44,972.46	15,447	191,184
Fare ($)	547.9	83.92	380	640
Unemployment (%)	7.13	1.38	5.14	10.93

3.2 Description of the model

The base form of the proposed model is

$$E_t = \beta_0 + \beta_F \ln\left(F_{t-1}\right) + \beta_T \ln\left(T_t\right) + \beta_D \ln\left(D_t\right) + \varepsilon_t \qquad (1)$$

where E_t is the estimated evasion in month t, $F_{t\text{-}1}$ is the lagged number of fare inspections carried out by the transit authority, T_t is the fare and D_t is the unemployment rate. The error term ε_t follows an ARMA process, the standard approach to modelling the errors in time-series models. The ARMA specification chosen was the one giving the best fit according to the Akaike information criterion.

In model (1) we consider the lagged number of inspections ($F_{t\text{-}1}$), given that a lag can be expected in the effect of the level of fare inspection on evasion. The motive for this lag is the idea that the level of inspection in a given month is not observable by users immediately but rather after the passage of some period of time, which for modelling purposes we take to be one month.

It is worth noting that when estimating multivariate regression models with cointegrated series, the estimates are "superconsistent". It implies that the estimates remain consistent even in the presence of endogeneity (contemporary correlation between the error and the regressors). Formal demonstrations can be found in Phillips and Durlauf (1986), or Stock (1987).

An extended version of the base model containing three additional variables representing the changes in the explanatory variables (first differences) was also tested. This formulation was specified as follows:

$$\begin{aligned} E_t = \beta_0 + \beta_F \ln\left(F_{t-1}\right) + \beta_{\Delta F} \Delta \ln\left(F_{t-1}\right) + \beta_T \ln\left(T_t\right) + \beta_{\Delta T} \ln\left(T_t\right) + \\ \beta_D \ln\left(D_t\right) + \beta_{\Delta D} \ln\left(D_t\right) + \varepsilon_t \end{aligned} \qquad (2)$$

Since the estimates were made with time-series data, the latter had to be checked for non-stationarity, and if found not to be stationary, then tested for cointegration to be sure the regression estimates would not be spurious (Granger and Newbold, 1974). For the non-stationarity check we applied the augmented Dickey-Fuller unit-root test, using the version with the intercept but not the deterministic trend term. Three lags were used as longer lag structures proved to have no further effect. The results of the test are given for each variable data series in Table 3. They show that three of the four series behaved in a way consistent with the presence of a unit root at a 5% significance level. For the logarithm of the number of inspections, the test rejected the presence of a unit root at a 10% significance level.

Table 3
Unit-Root Test Results

Variable	Z(t)	5% Critical Value	Approximate p-value
Evasion	-1.586	-2.904	0.4908
ln(no. of inspections)	-2.734	-2.904	0.0683
ln(fare)	-2.099	-2.904	0.2449
Unemployment	-2.183	-2.904	0.2126

One of the characteristics of series with unit roots is that their variances grow infinitely with the prediction horizon. This does not seem reasonable for variables such as evasion and unemployment, which by construction can only take values between 0 and 1. However, Campbell and Perron (1991) recommend treating data series by their behaviour in the finite sample. In the present case, the series behaved as though they had unit roots.

We therefore checked the variables in (1) for cointegration, which we did using the Johansen test (Johansen, 1991). Also known as the trace test, it is based on estimating a VAR model using maximum likelihood. We specified the model using a constant term and three lags of the endogenous variables. The test was first conducted with all four variables and then repeated using only the three variables that had a unit root at the 10% significance level on the augmented Dickey-Fuller test (Table 3).

The trace test results are shown in Table 4. Those given in Panel (*a*) are for all of the variables in (1), and since there are four, there may be as many as three cointegration vectors. In that case, the null hypothesis stating that there are no more than two such vectors is rejected, which constitutes evidence of cointegration. Strictly speaking, what the test rejects is that a possible third vector does not exist. The rule is that for estimating the number of vectors, the point of reference is that at which the null hypothesis is rejected. In the present case, therefore, there are two. For the three variables having a unit root at the 10% significance level, the results in Panel (*b*) show that there is one cointegration vector.

Table 4
Cointegration Trace Test

No. of cointegration relations	Eigenvalue	Trace Statistic	Critical Value
	Panel (a)		
	Variables: Evasion, ln(fare), ln(no. of inspections), unemployment		
None	.	61.4901	47.21
At most 1	0.31851	30.0456	29.68
At most 2	0.21438	10.2603*	15.41
At most 3	0.08966	2.557	3.76
	Panel (b)		
	Variables: Evasion, ln(fare), unemployment		
None	.	35.513	29.68
At most 1	0.2627	10.2180*	15.41
At most 2	0.07014	4.1823	3.76

* indicates rejection of the null hypothesis.

3.3 Results

The results for equations (1) and (2) are set out as Models 1 and 2 in Table 5. In both cases, the best fit was achieved using an AR(2) process for error term ε_t, although other ARMA specifications did not change the results appreciably. The roots of the autoregressive process are invertible, which is consistent with the results of the cointegration test. The estimates were derived using maximum likelihood and the standard errors were estimated with a heteroscedasticity-robust variance-covariance matrix. Models 3, 4 and 5 in the table each include a different one of the three first-difference variables to test separately the stability (robustness) of the estimates.

The results for Model 1 indicate that the marginal effects of the fare level and the number of inspections on evasion are significant. The coefficients of the logarithm of the variables are semi-elasticities. The estimates thus reveal that a 10% increase in the fare raises evasion by 2 percentage points while a 10% increase in inspections lowers it by 0.8 percentage points. These findings are consistent with the low inspection levels on the Transantiago bus system. It is not so much that the inspections are ineffective as that they are relatively infrequent, and in most cases fines for violations are neither large nor immediate. As regards unemployment, the coefficient is negative but not statistically significant.

Table 5
Estimates of the β-Parameters of the Models

Dependent variable: Evasion	Model 1	Model 2	Model 3	Model 4	Model 5
Ln(fare)	0.21*** (0.047)	0.24*** (0.057)	0.212*** (0.045)	0.203*** (0.052)	0.24*** (0.05)
ΔLn(fare)		-0.061 (0.165)	-0.054 (0.133)		
Ln(lagged no. of inspections)	-0.008*** (0.003)	-0.007 (0.005)	-0.008*** (0.003)	-0.006 (0.005)	-0.009*** (0.003)
ΔLn(lagged no. of inspections)		-0.002 (0.004)		-0.002 (0.004)	
Unemployment	-0.259 (0.328)	0.159 (0.414)	-0.273 (0.332)	-0.257 (0.317)	0.138 (0.398)
ΔUnemployment		-0.649* (0.34)			-0.662** (0.331)
Constant	-1.001*** (0.3)	-1.229*** (0.355)	-1.009*** (0.282)	-0.976*** (0.32)	-1.208*** (0.32)
AR					
Lag 1	0.58*** (0.116)	0.606*** (0.132)	0.592*** (0.123)	0.573*** (0.118)	0.591*** (0.11)
Lag 2	0.284*** (0.107)	0.243** (0.121)	0.27** (0.114)	0.286*** (0.107)	0.264*** (0.101)
No. of observations	85	84	85	84	85

Standard error in parentheses. Confidence levels: *** = 99%; ** = 95%; * = 90%; no asterisk < 90%.

The results for Model 2, which includes both the absolute levels of the explanatory variables and their first differences, diverge from those of Model 1 mainly in that unemployment—or more precisely, the change in it—has a negative impact on evasion that is statistically significant (6% significance level). In other words, an increase in unemployment leads to a decrease in evasion, and vice versa. This seemingly counterintuitive finding may be explained by the dynamic of persons in marginal or unstable employment whose jobs are particularly sensitive to changes in the unemployment rate and who have a greater propensity than the average user to evade due to economic necessity. When unemployment rises, such individuals are more likely to find themselves out of work and thus take buses less frequently relative to the rest of the users, while when unemployment falls the reverse is true. The coefficient of the unemployment change variable indicates that an increase of 1 percentage point in the unemployment rate reduces evasion by 0.65 percentage points. Since this variable is exogenous, it could be included as an input to the process of defining anti-evasion policies.

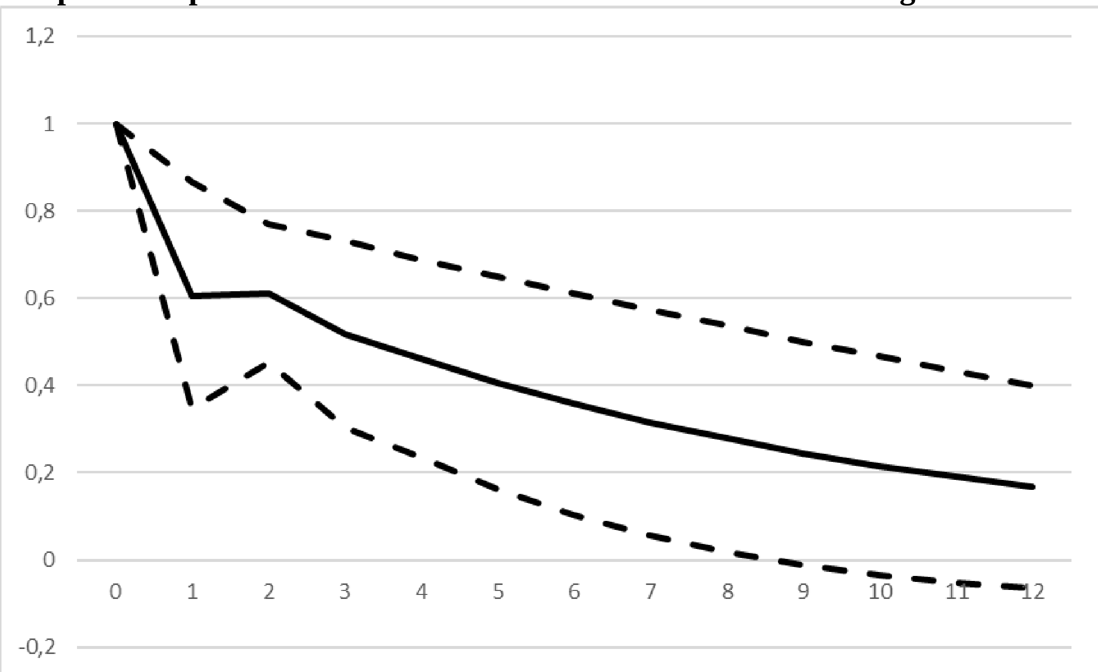
Another difference between the two models is that in Model 2, inspection levels are no longer significant. However, the joint effect of the inspection level and the change in it continues to be significant in reducing evasion with a 5% significance level. We interpret this to mean that with the inclusion of both variables, the collinearity between them reduces the power of the individual tests.[1]

Finally, Models 3, 4 and 5 confirm the estimates of Models 1 and 2.

To summarize, our estimates indicate that higher fares increase evasion; more inspection reduces it, although to a limited degree given Transantiago's currently low levels of inspection and small fines for violations; and a rise in unemployment may result in slightly less evasion.

Note finally that since our model is dynamic due to the structure of the error (second-order autogressive), a change in any of the explanatory variables will have an impact over time, not only in the immediate period. The trend of a one-standard-deviation shock in the evasion rate is illustrated in Figure 2, showing how it persists for 8 to 9 months.

Figure 2
Impulse-Response Function for a One-Standard-Deviation Change in Evasion



1 Although an integrated variable that behaves as a random walk will not exhibit correlation between its absolute level and its first difference, this was not the case for the Ln(no. of inspections) variable. The lag coefficients in the unit-root test were significantly different from zero. The correlation was 0.33, and the variable was the one that displayed the greatest reversion to the mean in the unit-root test.

With our estimates and some assumptions, it is possible to make a basic cost-benefit analysis of increasing the number of inspections. The total number of inspectors in Transantiago is close to 200, with a monthly gross salary of approximately US $ 600. This would cost US $ 1,440,000 a year. On the other hand, the loss of revenue from evasion is estimated at about US $ 200,000,000 per year. Therefore, if the number of Transantiago inspectors were doubled, spending on inspection would increase by US $ 1.44 million per year, and the loss of revenue would be reduced by US $ 1.6 million per year (-0.008 * 200,000,000). These gross benchmark results would indicate that the cost of increasing the audit would be similar to the eventual higher collection.

4. CONCLUSIONS

Evading fare payment on public transport is a growing problem that can contribute significantly to transit systems' financial deficits. Existing works have concentrated on the solutions that have been attempted by various systems around the world. The present study complements these previous efforts, presenting an econometric model with a cointegration analysis that identifies the long-term economic relationships between evasion and three key variables that could reasonably be expected to act as causal factors: the fare, fare inspection levels and unemployment. The model was estimated using data from the bus system in Santiago, Chile.

The first conclusion from the model results is that there exists a positive correlation between evasion and the level of fares. Our estimates indicate that a 10% rise in the fare induces an increase of 2 percentage points in the evasion rate (a semi-elasticity measurement). The second conclusion is that fare inspection is insufficient or ineffective for reducing evasion, at least in the case of Santiago. The estimates show that if the number of fare inspections on the system is doubled, its dissuasive impact on evasion would only amount to 0.8 percentage points (also a semi-elasticity). Our estimates suggest a revision of the evasion control policy in Santiago to improve its effectiveness.

We further conclude that there is a negative correlation between evasion and unemployment. This counterintuitive finding may be explained by the fact that those most vulnerable to job loss, and therefore more likely to evade than the average user, tend to reduce their use of the bus system when unemployment rises and increase it when unemployment falls.

A fourth variable, the public's evaluation of the bus system on a monthly survey, was also tested but found not to be statistically significant and therefore eliminated from our analysis.

These results should provide some useful indicators for decision makers charged with designing and executing mechanisms for controlling evasion on public transport systems. For instance, to link inspection efforts to fare increases and unemployment reductions. Our results could also be inputs for further developments of theoretical models based on individual preferences (structural relations).

ACKNOWLEDGMENTS

Rodrigo Troncoso acknowledges the support of Libertad y Desarrollo.

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APPENDIX

City	Evasion rate	Year	Source
Melbourne	5.0%	2015	http://ptv.vic.gov.au/news-and-events/news/public-transport-fare-evasion-at-lowest-level-on-record/
Seattle	4.8%	2010	http://metro.kingcounty.gov/am/reports/2010/FareEvasion04-10.pdf
London	1.3%	2013	http://content.tfl.gov.uk/STP-20131022-Open-Item07-Fare-Evasion-on-London-Buses.pdf
Vancouver	2.5%	2007	http://www.cbc.ca/bc/news/bc-080723-Fare-Evasion-pwc.pdf
Sidney	2.3%	2006	http://www.audit.nsw.gov.au/ArticleDocuments/138/150_Fare_Evasion.pdf.aspx?Embed=Y
Vienna	3.0%	2010	Wiener Linien (2010) Mehr Fahrscheinkontrollen, sinkende Schwarzfahrerquote, in: http://www.wienerlinien.at/eportal/ep/contentView.do/contentTypeId/1001/channelId/-8615/programId/22534/pageTypeId/9320/contentId/25239 (22.08.2012).
Cologne	4.7%	2012	Schlesiger, C. (2012) Undercover-Einsatz: Nahverkehr | Bus- und Bahnbetreiber erleiden hohe Einnahmeverluste durch Schwarzfahrer. Nun leisten die Städte Gegenwehr, WirtschaftsWoche 2012 (16), 16.04.2012, 58-59.)
Berlin	4.0%		
Bonn	3.9%		
Hamburg	3.5%		
Munich	3.0%		
Auckland	6.4%	2013	https://at.govt.nz/media/196871/agenda-item-9i-attachment.pdf
San Francisco	8.0%	2014	http://www.streetsblog.org/2016/06/21/mta-says-proof-of-payment-may-increase-fare-evasion-history-says-otherwise/
Reggio Emilia	43.0%	2012	http://dse.univr.it/workingpapers/wp2012n24.pdf
Lima	10.0%	2016	http://www.plataformaurbana.cl/archive/2016/05/09/santiago-presenta-la-mayor-evasion-de-latinoamerica-y-un-debil-sistema-de-multas-para-controlarla/
Buenos Aires	12.0%	2016	http://www.plataformaurbana.cl/archive/2016/05/09/santiago-presenta-la-mayor-evasion-de-latinoamerica-y-un-debil-sistema-de-multas-para-controlarla/
Bogotá	15.0%	2016	http://www.plataformaurbana.cl/archive/2016/05/09/santiago-presenta-la-mayor-evasion-de-latinoamerica-y-un-debil-sistema-de-multas-para-controlarla/
Santiago	27.6%	2016	Ministerio de Transportes y Telecomunicaciones, Government of Chile