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Short run fare elasticities for Bogotá's BRT system: ridership responses to fare increases

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Abstract

The fare policy of the BRT system in Bogotá, in order to cover its operating costs, has consisted of steadily fare increases, since its creation until 2012. To date, no study has been done to estimate the users' reaction to these changes in the short-term. That is, there is no information about price-demand elasticities. This issue should be a key factor in deciding on price changes and evaluating the impact of these changes on ridership. In the case of Bogotá's BRT (Transmilenio), estimating such elasticity is a need, but also a complex task: the travel demand is growing constantly and few fare changes happen at the same time throughout the whole system. To overcome this barrier, an econometric panel data model at station level was developed that takes advantage of highly disaggregated information on ridership for the Transmilenio system. The database provided information on entrances to the system's stations between 2001 and 2012 at the daily level (phases 1 and 2). Monthly information on other factors that may influence ridership, like fuel prices, unemployment rates, population and traditional bus fares, were also included. After the introduction of a fare increase, the elasticity's absolute value decreases from −0.565 (1 week) to −0.408 after a month. In addition, low-income users are more sensitive to these changes. We also test for differences between the effects during peak and off-peak hours. The results show higher values in the off-peak hours than in the peak hours. This should inform decision takers in Bogotá about the effect of fare changes on ridership responses and also on equity and accessibility.

Keywords BRT elasticity · Public transport elasticity · Short-term elasticities · Transmilenio · Bogotá

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Introduction

The impact that fare changes have on ridership (the number of trips) is an unsettled issue in the Colombian context. Theoretically, when the fare increases, the ridership tends to decrease. However, the magnitude of such a decrease is difficult to measure and can have strong variations between public transport systems and cities. It also depends on the traveler type, time of the day, day of the week, and trip purpose, among other individual characteristics of users, and finally on the extent of substitution between transport alternatives in the local context (Litman 2012). In the medium and long-term, a range of ridership changes may also be caused by other factors, such as an increase in car/motorcycle ownership rates.

The variables for which there is more information in the literature related with the public transport ridership response are the fare, the household income and the level of service. In the international context, there are several classic reviews about this issue. For example, Oum et al. (1992) and Goodwin (1992) summarize some of the major studies on price-demand elasticities for transport, emphasizing differences over time. They review more than 50 research reports on the influence that fares have on the public transport demand. There are also several meta-studies in the UK, Europe, USA and Australia (Hensher 2008; Holmgren 2007; Nijkamp and Pepping 1998; Wardman 2014). Holmgren (2007) finds that the estimated short-term fare elasticities range from −0.009 to −1.320, being more inelastic (ceteris paribus) in the USA and Australia than in Europe. Hensher (2008) compiles direct elasticities associated with the public transport choice and demand in three classes of direct elasticities. He finds that the major influences on the elasticity estimates are the time of day, the data type, the unit of analysis, the trip purpose, the geographic context, and the specific transport mode. Paulley et al. (2006), obtain similar findings, with an elasticity value around −0.4 in the short run. Additionally, mandatory activities tend to have lower elasticity values; the elasticity values and their effects are not symmetric, and bus and metro services could have different elasticities. There is a very interesting experiment in Tallinn, where Cats et al. (2017) examines travel pattern changes after the introduction of free-fare public transport policy.

There are also several local studies, such as that Savage and Miller (2017), where they study the ridership response to fare changes on the Chicago mass-transit rail system, as the fare varies with the per capita income in the neighborhood surrounding each station, between 2004 and 2013. They obtain mixed findings, in which for one of the fare changes the decline in ridership was greater in lower-income neighborhoods. For other fare increases, they find a relationship between income and ridership response. Pham and Linsalata (1991) provide a set of fare elasticity estimates for bus services in several USA cities during peak and off-peak hours using an ARIMA model in 52 public transport systems to try to isolate the impacts of fare changes. They find an average elasticity value of around −0.4 and report that users in small cities are more responsive to fare increases (−0.430, with a standard deviation of 0.189) than those in large cities (−0.361, standard deviation of 0.154). Notice that these standard deviations imply that 70% of studied cities have elasticities between −0.582 and −0.224 (the rest are more extreme values). The first one being 2.5 times bigger than the second one. From a policy perspective, a precise estimation of the particular elasticity system is then quite relevant.

Cordera et al. (2015) show how the per capita income levels and unemployment rates influence the demand for public transport in Santander (Spain). They suggest that, in periods of economic crisis, public transport operators can attract greater ridership, using factors like fares and service levels. Wang et al. (2015) use exhaustive public transport card data to assess the influence of distance-based fare increases on ridership and revenue and then evaluate three fare increase alternatives in terms of their impact on ridership and revenue. They find, among other results, that long-distance trips (around 10 km) are very sensitive to fare increases, with elasticities of around −0.8.

In Tunisia, Daldoul et al. (2016) uses a dynamic panel model to explain the mobility behavior towards the public transport supply of twelve cities. They found the price elasticity is around −0.4 in the short-run. De Grange et al. (2013) estimate the elasticities in the Transantiago public transport system by testing three alternative discrete choice models. Also in Transantiago, Batarce and Galilea (2018) estimate a demand model, which delivers information on the demand price elasticity and the effect of other variables related to the supply. They found that a fare composed of a fixed and variable part, leads to a demand level 14% higher than the level based on actual fare.

As we have seen, although the literature on the impact of fare changes on ridership is well known, there is a complete lack of published studies on the impact of the public transport ridership response to fare changes in bus rapid transit (BRT) systems in Latin America. Many studies provide evidence about the influence of different variables on the public transport demand; however, to the extent of our knowledge, this is the first one for the Colombian and BRT case. It is important that transport planners are aware of the fact that fare policies have a great influence on the ridership response. Benefits from BRT systems are often skewed toward medium-income population and thus less progressive than they might be (Venter et al. 2017). They argue that one of the reasons may be the inappropriate fare policies.

Perhaps, the paper from de Grange et al. (2013) is close to ours in terms of dealing with the elasticity of a public transport system in Latin America. Our approach improves on their proposal, mainly because of: (1) the quality of our data and our econometric approach allowing us to use all the information from fare changes during a long period: 2001–2012; (2) the inclusion of other variables that could influence the demand that are controlled even if they are not observed using the location of each system station; (3) the fact that we can incorporate weekdays and weekends into our estimation; and (4) the ability to report differential fare effects for high and low-income areas.

In Bogotá, most of the daily trips were provided by its public transport system (almost two-thirds of motorized trips), with a high level of use by the low-income population. The backbone of the public transport system is Transmilenio (TM henceforth), a BRT system. In recent years, its financial performance has been declining. This has been attributed to the rapid growth in the number of users, the lack of infrastructure, and the rising costs of its private operators. These have brought fare changes to the forefront of the local public and political discussions, as the need to increase the revenue of the system conflicts with the costs of the system for low-income users.

The TM system has higher fares than traditional buses and, in some corridors, can compete with traditional routes. The TM fares have increased steadily in recent years and currently do not fully cover the operating costs. In addition, the TM system has an integrated fare, which makes it difficult to evaluate the impact of fare changes on ridership, as Shiftan and Sharaby (2012) points out. In this study case, every fare change affects the whole system at the same time. Then, there is no opportunity to see what would have happened if the fare were not changed, so there is not a straightforward control group.

This research focus on the short-term implication of fare increases on BRT system in Bogotá. Originally, when these changes were made there was one desired objective: cover the operating costs of the system, without consider the implications on ridership response. The purpose of this paper is to estimate the price elasticity of the demand for TM using the travel demand and respective fare increases over time (between one and 4 weeks) in conjunction with other related elements, like fuel prices, regular public transport fares (traditional buses), unemployment rates and population. The analysis period was between January 2001 and July 2012. The proposed methodology does not use information on travel times, trip purposes or services supply, because these data are not available at the spatial level as the data on ridership. Nonetheless, given the structure of the data set, the proposed model can deal with some unobserved variables at the station level and that could affect the proper identification of the elasticity.

Even with the presence of a large dataset of daily entrances at the station level for a long period, getting proper estimations of the elasticity levels is not a straightforward task. This is due to the absence of information on a multitude of factors that vary at the user level (i.e. education and income levels), going through the station level (i.e. main trip purposes), and ending at the whole city level (i.e. trends in car/motorcycle ownership). These factors affect ridership and are not directly observable. Devising a model that takes account of the data meaningful variation at the same time that controls and corrects for biasing ones, was a challenge that was solved methodologically by transforming data, selecting a subsample(s) and using the correct econometric model, as will be explained later.

Our results are not only important in the local context in which this information is lacking but also add to the evidence of public transport elasticities for big cities in developing countries for which evidence is still scarce. There are remarkable differences between Latin American contexts and the ones from developed cities for which there is ample data on public transport elasticities. Overcrowding, financial deficits, lack of coverture, competing public transport systems, and the low-income levels of most users, are constant problems in the first case (developing cities), and are particular problematic in Bogotá. Due to these issues, the fact that public transport systems in such cities have comparable ridership response to fare changes should be taken as an empirical endeavor and not as an already answered one. This article provides sound evidence in this regard.

This paper begins by a description of the public transport system in Bogotá, and particular of the TM system, a detailed description of the fare structure and the principal ridership trends is also described. A description of our data is then provided, followed by the description of the methodology implemented. The principal point here is to show the richness of the data and how this information in combination with our method allows to get precise estimation of the reaction of users to price changes in the short term. We finalize with a discussion of the implication of these results for the local context.

The Bogotá transport system

Bogotá is a city of 8.0 million people and an urbanized area of approximately 380 km^2. It is currently a conurbation with several surrounding municipalities, reaching a population of around 11 million people. The most important of these municipalities is Soacha (see Fig. 1), which, with about 510,000 inhabitants, in practice is part of Bogotá city, forming a functional area that is gradually emerging as the city extends beyond its administrative boundaries (Guzman et al. 2017a). The TM trunk corridor in this neighboring city began operating in late December 2013. This "megacity" shares most of the problems of megacities over the world: high travel times (even in a relatively compact city), high spatial segregation, low access levels (especially for the low-income population), low road safety indicators, and poor air quality.

On a typical day in Bogotá in 2015, according to the last mobility survey (SDM 2016), about 14.9 million trips were made, of which 45% were made on public transport: 27% on regular buses, 18% on TM and feeder lines and 0.5% by intermunicipal transport). Another 33% of trips were made by walking and cycling. Private cars, motorcycles, and taxis complete the modal split. In relation to 2011, TM increased its participation by 3.7% in 2015. Motorcycles rose from a share of 3.1% to a share of 5.5%. It was identified that about 92% of public transport users belong to the lower socioeconomic levels.

The Transmilenio system's characteristics

To initiate a structural change in transport conditions, the TM system in Bogotá began operations on 18 December 2000. A complete description of TM and its key features (phases 1 and 2[1]) can be seen in Gilbert (2008) and Hidalgo et al. (2013). Since its opening the total number of users of TM has been increasing steadily. At the same time, there has been a moderate expansion of the TM system during the last 15 years, including the construction of new trunk lines (phase 3, Soacha and some minor extensions) and stations and the implementation and growth of a bus feeding system. These two factors make it difficult to measure the response of the demand to fare increases using the consolidated figures for the whole system.

The TM network is composed of 112.5 km of trunk corridors, 663 km of feeder lines, and 148 stations (divided into 3 construction phases and currently with 19 private operators) and moved about 2.25 million passengers per day in 2015, including the trunk corridor in Soacha. The system works on average for 18.5 h a day on weekdays, between 04:30 and 23:00 h, with an average commercial speed of 26 km/h in 2015 for the whole system. Until August 2012 the TM system fares have increased to try to cover the operation costs, without any study of their impact on the passenger demand.

The inability of the TM expansion to keep up with the growing number of users has led to increased congestion in the system as well as wider operational problems, which are reflected in a negative perception by users (Guzman et al. 2018b). Despite this, TM continues to gain market shares at the expense of traditional public transport, although it is not ahead of private transport alternatives: cars and motorcycles.

In addition to the TM network, the Fig. 1 (left) shows the proportion of low-income zones, which earn less than USD 635 per month (≤ 50th percentile). This spatial distribution is classified into urban "zonal planning units" (UPZ), which are territorial units for planning the urban development at the local level, including predominant land-uses and main activities. As it can be seen, economic segregation is widespread in the city, with the low-income zones located in the urban periphery (mainly southwest and south, in Soacha, where 86% of the total households earn less than 620 USD/month, and some in the extreme north); whereas the richest areas are in the north and around the city center (Guzman and Bocarejo 2017). According to the available data, most (82%) of the households in Bogotá earn less than 1050 USD/month. This shows significant inequalities in income distribution: around 5% of the households have a monthly income above USD 2100. This spatial distribution of income levels will be useful when analyzing TM stations.

[1] Our study only covers these two phases. Currently the TM system has three phases and a connection with a neighboring municipality (Soacha).

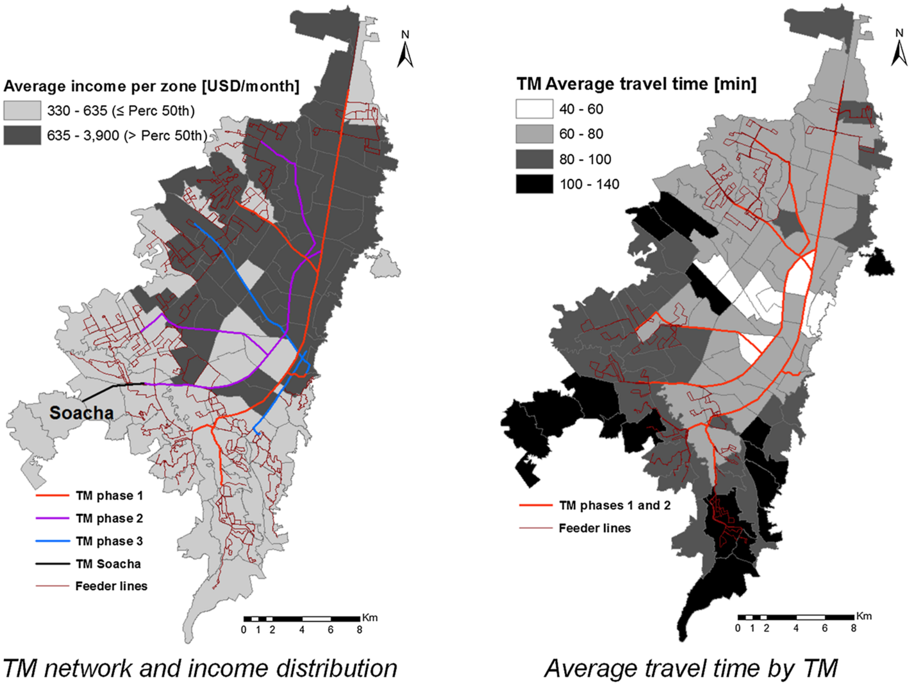

Fig. 1 TM network (trunks and feeder lines) and travel times

Because of high level of spatial aggregation available for the average household income, the fact that the same UPZ includes several TM stations and most of the stations are located just at the border between UPZ (with different socioeconomic characteristics), it was not possible to consider more disaggregated income segments. This is the reason why it was decided to use these aggregate income segments. However, the low-income segment is very similar to used in previous work (Guzman and Oviedo 2018).

In addition, significant differences were found in the travel times by TM between different zones of the city (Fig. 1, right). The travel times were obtained directly from the Bogotá Mobility Survey 2011 and averaged at the zone level. As reflected by these results, a TM user in a low-income zone spends 36% more time traveling on average than a user in a wealthy zone.

Currently, TM has high levels of congestion. Moreover, this problem in peak hours is increasing. The peak demands have become more acute; in 2002 the average boardings during the peak period represented 9.5% of the daily boardings, in 2008 they represented 12.0% (Hidalgo et al. 2013). In 2015 they reached a level at which the trips made in this period account for around 50.0% (or more) of the total daily travel demand met by TM (Guzman et al. 2018a). As the TM agency regularly increases fares to balance budgets, it may place extra strain on the system demand, producing negative effects in the medium and long term.

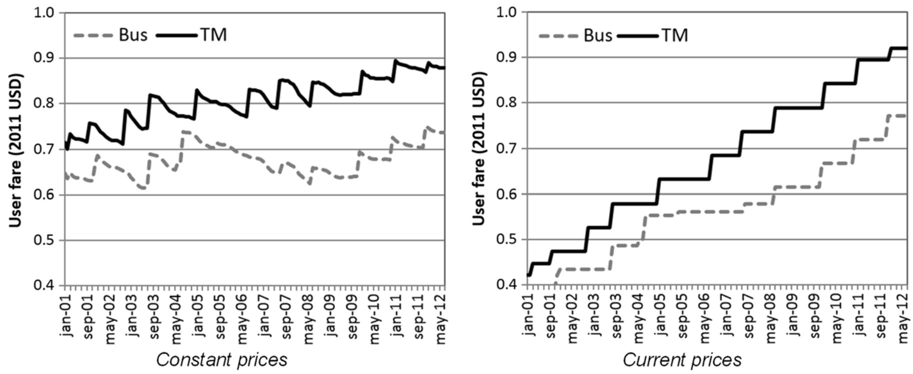

Fig. 2 Public transport user's fare

The fare structure

Many different fare schemes are used by public transport agencies with varying impacts. In the TM system, at least until August 2012 and after 2015, flat fares and fare integration were the fare strategy to benefit poor users, supposedly by cross-subsidizing the long trips of the poor with the short trips of the wealthy (Venter et al. 2017). Between August 2012 and January 2015, the fares changed in peak hours and in off-peak hours.

Figure 2 shows the user fare evolution in 2011 USD prices between January 2001 and July 2012 for TM and the regular public transport (bus) system. The last increase in the user fare (during our analysis period) was carried out in January 2012 (from 1700 to 1750 COP, approx. USD 0.92), and since then the technical fare (cost per passenger transported) has followed also a growing trend.

Once the technical fare rise has been identified, the increase in the user's fare cannot be implemented immediately. The fact that only nine fare changes have taken place during a 12-year period reflects this problem. The local government must approve public transport fare changes, making them a political instrument (of hard acceptance for the voters). This makes fare increases a slow process that can take a long time between the decision and its implementation and does not always produce the technically recommended change. The longest period without a fare change was 29 months, and the shortest one was about 9 months.

These system rigidities make the system response to a growing demand a slow process. In the short term, other than a reorganization of routes aiming for better efficiency there are not much leeway for the system managers. In the mid and long-term, increases in the vehicle fleet, opening of new corridors and stations were strategies that try to cope with the increasing demand of users.

The passenger ridership

In 2015 984 million passengers were mobilized in the TM system. This represents an increase of 8.8% over 2014 (in 2013 there were 840 million). The trunk corridors mobilized 690 million passengers and the feeder lines 294 million, representing growth of 9.8% and 6.6%, respectively. The number of passengers using the TM system has increased

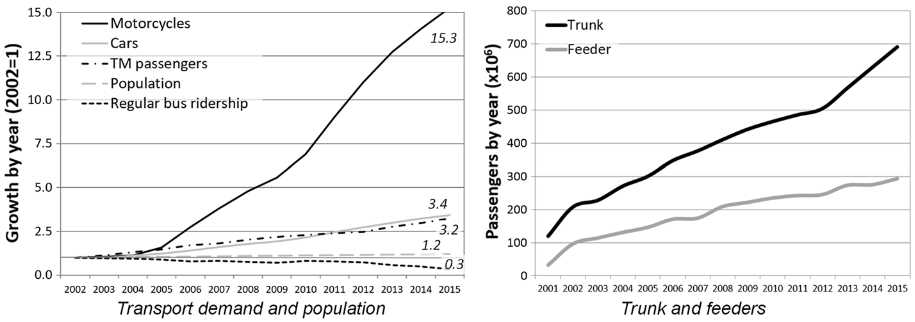

Fig. 3 Travel demand of transport in Bogotá and other indicators

consistently since its opening, even faster than the increase in the population, and the traditional public transport system is losing users quickly (see Fig. 3). It should be noted that in 2013 the Integrated Public Transport System (SITP in Spanish) began to be implemented, which transported 418 million passengers in 2015 (Guzman et al. 2018b).

As mentioned earlier, there has been an increase in the peak concentration (5:30–8:30; 16:30–19:30): in 2012 819,000 passengers were counted on average at peak hours (working day), representing a 1% increase over the previous year and more than 50% of the daily travel demand (Guzman et al. 2018a). The flow of passengers during these peak hours is double that in off-peak ones.

These trends show that the total number of passengers carried by regular buses has decreased constantly. Two reasons seem to be at play: (1) the start of the implementation in 2013 of the SITP, which aims to unify the public transport fleet and implement an integrated fare for the operation of all its public transport subsystems, and (2) the strong growth of motorcycle and car fleets in the last 10 years.

Methodology and data

This study is an aggregate fare-demand analysis. This type of analysis has advantages and disadvantages. The main point is that, while we can obtain reliable estimators of the short-run elasticities, we gain them at the expense of being able to say anything about the medium, or long run effects. For longer time windows that those used (more than 4-week), any reported effect would be also including the reaction of the system, so it is more likely to be the net effect of the changes in the fare after the system began to react. In strict terms we are only estimating the changes due to the rise in the fare and obtaining answers concerning the average response in the demand to changes of around +10% in the fares, which are the level of changes observed during the study period (see Table 1). It is not clear that such results could be extrapolated linearly to far bigger changes, for example a ±30% change in fares.

For the estimation of the elasticity of the TM system, it is possible to assume that most of the effects come from changes in the demand, particularly in the short-run window that is implemented in this study. Fare prices are not the result of an open supply and demand market. Instead, those policies are the results of authorities' decisions based on technical analysis of the operational costs and political considerations. This means that we do not expect changes in the supply side to be affected by the fare change. We also know that the technical fare is calculated monthly, so, for the shorter time windows (as in this case) it is highly unlikely that the system made any changes in reaction to the changes in ridership.

In the mid and long-term users' reaction to fare are not identifiable because other than the fare, there are several factors that are also affecting the ridership. There are some coming from changing alternative transport availability: reduction in price of motorcycles, changes in the efficiency of traditional bus systems, or greater use of the bicycle. Other are coming from other factors that affects the non-monetary costs of the system: increasing crowding levels, new corridors that increase the easiness to access new places, or improvements in integration of transport systems.

The data

The data to which we had access report the number of entrances for the TM system (just in trunk corridors) by individual station and day in a 12-year period from January 1, 2001 to July 31, 2012, with more than 588,000 individual observations. Because TM stations do not require card validation to leave the system, only the raw number of passengers is available without any type of identification of the origin-destination flows, socioeconomic characteristics, or travel purpose. This data is very precise as it comes from the registration that every user makes of a traveler card every time they enter the system.

The dependent variable used in the estimation of the model is the total number of incoming passengers during the day in each individual station of phases 1 and 2. This variable allows us to use the full variability of the data and was chosen among some other demand indicators, such as the total number of passengers mobilized, passenger-kilometers (which also include aspects related to the supply of the service), or others like operator revenues (which are affected by the pricing policy).

Figure 4 shows the time-series properties of this variable, both by month and by day of the week. By differentiating the total number of entries by station, the long-run growing trend disappears, and the month and day of the week cycles are easily perceived. On the left side, the month cycles are represented, with the vertical red lines identifying December. The graph on the right represents a day of the week cycle, with the vertical red lines identifying Sundays. It is this cyclic nature of the data that we will use to support our estimations.

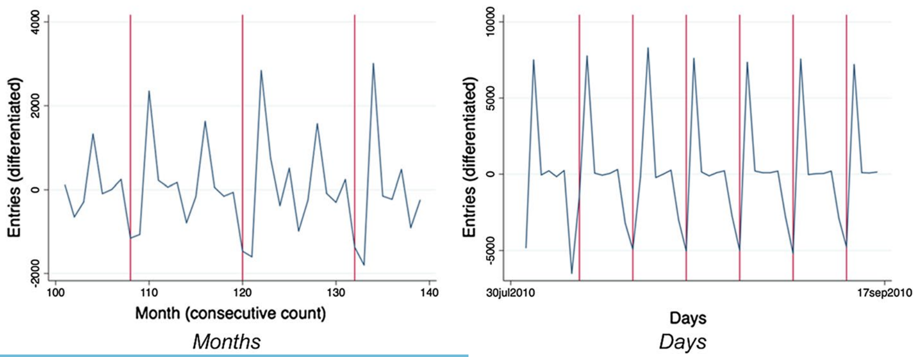

Fig. 4 Cycles over months and days of the week

Theoretical model

To assess the impact of the fare increase, and respectively the fare elasticity, a panel data model from our data sample was specified and estimated. One of the most remarkable features of the economic literature is the wide variety of impact models proposed, which is mostly linked to the choice of aggregation level of the data and to the choice of functional form. Indeed, differences in the types of data and in the model specifications are likely to affect the empirical results applied to relevant transport policies' analysis, such as elasticity values and traffic forecasts.

Among the advantages of the data set are the variability that it involves and the long-run data (12 years) of daily information. As we try to address the issue of the pure price effect on the demand, we must control many factors that could also be affecting it. Considering that we have multiple records for each unit of observation (the station), it is possible to use a fixed-effect econometric model. This type of model allows us to control for factors that are related to the specific social context of each station, which could affect the demand and which are constant over time (Cameron and Trivedi 2005; Wooldridge 2010). Examples of this refer to aspects such as the type and travel time, relative income levels between stations, and other social characteristics in users' profiles.

Particularly important is the fact that we are measuring short time periods (the shortest one is 1 week after the implementation of the fare change). The measurement of the technical fare and the IPK that are used to program the operation are made on a monthly basis, so our shorter measures are the effects even before the system makes any change in operation to adjust to the new conditions. For longest measures (more than 4 weeks), it is possible that some changes in operation are made as the results of the higher fare and the changes in demand, with the potential of improving the users' experience and decreasing the net effect of the fare increase.

Nonetheless, even with a clean estimate for shorter periods, the problem that remains is that there is not a straightforward control group. As every change in the fare affects the whole system at the same time, there is no opportunity to see what would have happened if the fare were not changed on that specific date. Consequently, we must find another way to reproduce this control group synthetically. A difference-in-differences (Cameron and Trivedi 2005) synthetic estimation is implemented, taking advantage of the cyclic properties of the data within the context of a fixed-effect econometric approach.

The main point of this approach is to identify the short-term properties of our data, while at the same time using as much information as possible of the large database available. This allow us to overcome the deficiencies related to small databases where only before and after estimations are possible, deficiencies that make estimation more sensitive to possible biases coming from unobservable characteristics.

The econometric model takes advantage of the variability present at the moment when the fare change is introduced. There are data at the level of day and station for the first two phases of the TM system. An analysis of the fare changes reveals that it always happens on the first day of the month and that the month in which it is applied is not always the same. This variation in the time of the fare change is the key to our estimation (see Table 1).

Table 1 Dates of changes on fares

Date of fare change	Day of the week	Fare change (%)
October 1st 2001	Monday	+5.8
November 1st 2002	Friday	+11.1
August 1st 2003	Friday	+10.0
January 1st 2005	Saturday	+9.1
August 1st 2006	Tuesday	+8.3
July 1st 2007	Sunday	+7.7
July 1st 2008	Tuesday	+7.1
January 1st 2011	Saturday	+6.3
January 1st 2012	Sunday	+2.9

The chosen approach is to measure the differences in the counted entrances by station between the days after the fare change and the days before it and to compare this with the identical difference in those periods in which there was not a fare change. As the fare change in all the stations occurred at the same time, with this proposed model, our controls will be the differences in the same days of the month and in the years in which there were no such fare changes. As there are 12 years of data, for each fare change, there are as controls between 9 and 11 years in which the change did not happen in such a month. Hence the reason for calling it a synthetic diff-in-diff: what would have happened on a specific date is reconstructed with information from the same month from different moments in time (both before and after).

It is essential to notice that the simple measuring of the days before and after the day of implementation of a fare change is not a good solution. Given the cyclic properties of the data (see Fig. 4), one cannot expect that such a difference will be zero, even in the absence of constant ridership growth. The construction of controls that give us information on the size of such variation for different moments in the year when no fare change is present solves this problem.

This difference has another advantage: it controls the constant growing trends of ridership in time. A log transformation is performed so that the dependent variable (daily trips by station) can be read as the percentage change between before and after a specific moment in time (which is the first day of the month). This makes the estimation independent of the specific level of trips for that day and station, making it possible to build our control from data at different points in time. The same argument is valid for the TM fare, fuel prices, regular buses fares, unemployment rates and population, which are not measured directly but as a proportional change before and after a specific moment in time. Level measures do not work because the big change in users by station make non-comparable the beginning of the analyzed period (2001) and the end of it (2012).

Even when the ridership growth tendency is controlled with our variable specifications, it remains a cyclic trend by the day of the week and the month of the year. To be able to control this seasonal factor, dummy variables that identify when an observation corresponds to a particular day of the week, month, and year are implemented. This is because the fare changes vary throughout the day of the week and month, and such effects could be isolated from the one produced by the fare change.

Figure 5 represents the estimation approach. The regression calculates the effect that one increase in the fare has on the (B-A) difference for each day of the week, taking account of the differences due to the day of the week, month, year, and station. This aggregation by day of the week takes account of the cyclic weekly properties of the series. It conveys more

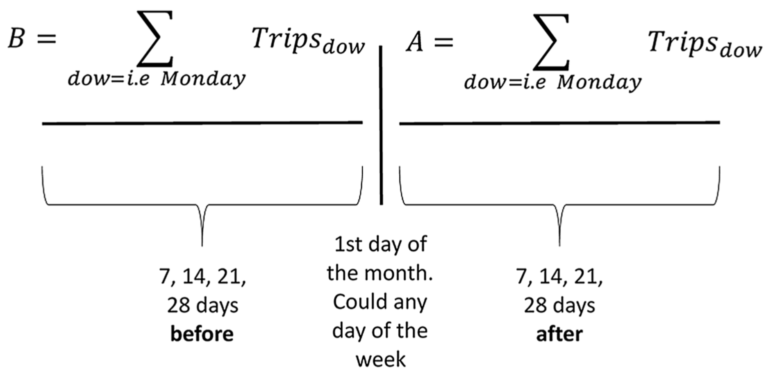

Fig. 5 Estimation approach

information to our estimation than trying to average out the weekly cycle simply by using whole weeks instead of days.

Time windows of 7, 14, 21 and 28 days (1, 2, 3 and 4 weeks) are used. The shorter the time window, the more easily we can sustain that we are seeing a pure effect of the fare but at the cost of higher-level noise (the error term) in the data that decreases the accuracy of the estimation. This also means that for each specification we are discharging all the information that is not within the time window.

It is worth stressing that this approach using the cyclic properties of the data eliminates their medium and long-term properties. This implies that the short-term effect of the fare is measured by controlling and discharging information that relates to the medium -and long-term impacts. These last two effects are much more difficult to detect and need a totally different approach, because in longer periods the system itself changes in response to the changes in users. The proposed econometric model is the following:

$$\Delta t_{idmyx}\left(:\ t_{idmyx}(A) - t_{idmyx}(B)\right) = \beta_0 + \beta_1 \Delta p_{my} + \beta_2 \Delta g_{my} + \beta_3 \Delta b_{my} + \beta_4 \Delta u_{my} + \beta_5 h_{my} + \sum_{d=1}^{7} \beta_{6.d} dow_d + \sum_{m=1}^{12} \beta_{7.m} mth_m + \sum_{y=2001}^{2012} \beta_{8.y} year_y + v_i + u_{ij}$$

where t_{idmyx} is the logarithm of trip entries to a station i for each day of the week (d = Monday, Tuesday…, Sunday) in the lapse of x = 1, 2, 3 and 4 weeks after or before the first day of a particular month m and year y. The logarithmic difference change in the fare is Δp_{my}, which is zero (0) if no such change took place at that moment. It is the same for fuel prices (Δg_{my}), regular bus fares (Δb_{my}), unemployment rates (Δu_{my}) and population (h_{my}). The available population measure has a year-temporal resolution, so it is not possible to use it as a difference. The dummies for each day of the week are dow_d and the dummies for each month are mth_m. For each year, the dummies are $year_y$. The fixed effect of every station is v_i and finally u_{ij} is the error term.

We run separate regressions for two different levels of income: above and below the median (see Fig. 1). A joint regression is not possible, as we are using a fixed-effect regression that is not able to give information on constant characteristics per observation (i.e. the relative income level of the station's immediate social context).

Table 2 Principal variables description

Variable	Obs. (N)	Mean	SD	Min.	Max.
Entrances	370,265	9893	12,806	0	189,588
TM fare	11	1300	317	850	1750
Fuel	12	5920	1725	3125	9040
Bus fare	12	1060	227	750	1467
Unemployment*	156	14.06	2.77	8.9	20.9
Population**	1573	57,943	52,365	845	325,539

*Unemployment rates at city level

**Population at UPZ level

Table 3 Full results for 4 weeks window specification

4 weeks regression		Full data	Income ≤ 50th percentile	Income > 50th percentile
TM fare	Coef.	−0.408***	−0.534***	−0.366***
	p value	(0.00)	(0.00)	(0.00)
Fuel	Coef.	+0.327***	−0.015	+0.504***
	p value	(0.00)	(0.92)	(0.00)
Bus fare	Coef.	+0.811***	+0.703***	+0.863***
	p value	(0.00)	(0.00)	(0.00)
Unemployment	Coef.	−0.301***	−0.264***	−0.315***
	p value	(0.00)	(0.00)	(0.00)
Population	Coef.	0.000	0.000	0.000
	p value	(0.13)	(0.66)	(0.12)
N		31,086	9999	21,087
R2		0.224	0.284	0.208
Fixed effects		Y	Y	Y
Time controls		Y	Y	Y

p values: *$p<0.10$, **$p<0.05$, ***$p<0.01$

Table 2 presents the principal variables of our estimations. Trips are reported as individual entries to each station, fares are in current Colombian pesos (COP), fuel prices is in COP/gallon, unemployment rates in percentage of the active population, and population in inhabitants by zone (UPZ). Those variables are log transformed and differentiated to be used in our model and to produce the estimates that we report in the results section.

Analysis of results

Our main results are presented in Tables 3 and 4. According to our approach, in which we measure our principal variables (trips and fare changes are in logs), both must be interpreted as percentage changes, and the regressions give us a direct approximation of elasticity values. Table 3 reports the full results of our analysis using a 28-day time window.

Table 4 Elasticities by time window and income group

Time window		Full	Income ≤ 50th percentile	Income > 50th percentile
1 week/7 days	Coef.	−0.565***	−0.447***	−0.603***
	p value	(0.00)	(0.00)	(0.00)
2 weeks/14 days	Coef.	−0.590***	−0.635***	−0.571***
	p value	(0.00)	(0.00)	(0.00)
3 weeks/21 days	Coef.	−0.296***	−0.396***	−0.259***
	p value	(0.00)	(0.00)	(0.00)
4 weeks/28 days	Coef.	−0.408***	−0.534***	−0.366***
	p value	(0.00)	(0.00)	(0.00)

p values: $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

An interesting finding has to do with the positive and significant coefficients of the regular buses. This indicates that regular buses can replace TM (this transport mode is a substitute). If the TM fare is increased, users will look a mode to replace it, since the substitute mode will increase its ridership. If the increases are above the payment capacity of the users, it is likely that in the medium and long-term, they look for drastic solutions such as buying a motorcycle. Regarding fuel variable, the general coefficient (full data column) is statistically significant. However, the coefficient for the low-income group is not. This could indicate that car is also a substitute, but only for the high-income group (around 45% of this group use car as a preferred transport mode). We also observe that population is not statistically significant.

Table 4 shows the results of the elasticity when the time window varies. The general coefficient (full data column) relative to elasticity is negative, as expected, and statistically significantly different from zero (at 99%***) in all cases. These results are coherent with values found in other contexts and show that a change in fare does have an important effect on TM ridership.

We observe higher elasticity (a stronger response to the change in fares) in the low-income subsample. This show a relationship between income group and ridership response. This is consistent with the idea that the same fare change is a proportionally larger part of the income for a lower-income household than for a high-income one. These results also support the idea that low-income households are strongly hit by an increase in the fares.

In line with the evidence from the wide literature on public transport elasticity estimation, the short-run elasticity is inelastic (absolute values less than 1). But, at least in the very short run (less than a month), higher than is found in other contexts, in which it is around −0.3/−0.4 (de Grange et al. 2013; Hensher 2008; Paulley et al. 2006). Thus, increasing fares is a policy that immediately induces users to reduce the use of the TM system. Nonetheless, the increase in price more than offsets the decrease, leading to an overall increase in the resources collected (at least shortly). We consider some variants by trying to assess separately the effect by income and the temporal effects regarding the impact of a fare increase, which reflect an accurate reaction of users. The results suggest when the rate increases by 1%, 0.57% of users leave the system in the first week. However, by not finding a viable substitute transport mode, we suppose they return to the TM system.

To get a better perception of the change in the elasticities by income group, we use the average income for the zones (UPZ) in which each station is located and interacted it with

Table 5 Interaction of elasticities with income levels

Variable	Variable	3 weeks	4 weeks
TM Fare	Coeff.	−0.451***	−0.537***
	p value	(0.00)	(0.00)
Income	Coeff.	−0.0001*	−0.0002***
	p value	(0.05)	(0.00)
TM Fare × Income	Coeff.	0.00016**	0.00018***
	p value	(0.04)	(0.00)
Obs.		31,246	31,099
R2		0.280	0.266

p values: *$p<0.10$, **$p<0.05$, ***$p<0.01$

Table 6 Peak and off-peak elasticities by time window and income group

Time window		Full data		Income ≤ 50th percentile		Income > 50th percentile	
		Peak	Off-peak	Peak	Off-peak	Peak	Off-peak
1 week/7 days	Coef.	−0.562***	−0.441***	−0.519***	−0.386***	−0.567***	−0.461***
	p value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2 weeks/14 days	Coef.	−0.691***	−0.549***	−0.708***	−0.598***	−0.680***	−0.534***
	p value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
3 weeks/21 days	Coef.	−0.336***	−0.308***	−0.382***	−0.431***	−0.318***	−0.268***
	p value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
4 weeks/28 days	Coef.	−0.483***	−0.366***	−0.609***	−0.502***	−0.433***	−0.327***
	p value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

p values: *$p<0.10$, **$p<0.05$, ***$p<0.01$

the fare change. In this way, we have a test of the statistical significance of these elasticity changes as average income increases. Table 5 shows the results for the model with three and four-week time windows were significant. These results go in the same direction that the ones in the previous table: the absolute size of the elasticity reduces as the zone in which a station is located, increases in its average income.

We also test for differences between the effects during peak and off-peak hours (see Table 6). Although the change in the fare is the same, the ridership profile is different, so this could mean that some types of rides (according to the trip purpose) are more affected than others. The results show higher values in the off-peak hours than in the peak hours. This is because during the peak hour work and study purposes dominate, while in the off-peak periods there is a greater proportion of trips with other purposes. The results also show that for higher-income households there are no important differences between the two periods, but for lower-income ones the longest analyzed period result (4 weeks) is that the off-peak period's ridership is more affected than the peak periods. This result is consistent with the greater impact on this segment of the population and a possible choice to reduce non-essential travel as a response to the higher costs.

The effects also vary when the time window is extended. Changes in the effect of this time variation suggest different reactions according to the perception of the fare increase. In the 2-week time window, the elasticity is higher than in the other time windows (−0.69).

It is also higher in peak hours, because in those periods, most of business and study travel are made, which are less price sensitive.

Users are probably driven by the existence of several differences during the month in terms of money availability (income), since people in working classes are paid on the fifteenth and the thirtieth day of the month. This may suggest that, in the second and fourth weeks after the fare increase, the availability of money is reduced and a small difference in the fare is significant for the demand behavior. Considering that all the fare changes take place on the first day of the month, there is no possibility to control for these factors.

In particular, within the urban transport networks, it seems important to differentiate the immediate effect and the decline of the effect as time passes. This is coherent with the impossibility of having significant variations in commuting trips in urban centers due to specific reasons (e.g., work or study), while another trip purpose, such as leisure or shopping, may be more likely to be avoided or shifted to some other transport modes.

Fare increases prompt an immediate reaction from users. Elasticity in the TM system has a cyclic behavior whereby users react to increases and then the ridership stabilizes. After long periods without fare increases, a new change is often highly criticized in the public debate, but, at the same time, the longer the time without an adjustment to the fare, the larger the gap between the user fare and the technical fare of the system. The demand of the TM system increases every day, and some other changes have been performed to control the extreme conditions in peak periods. Some of these analyses suggest that it is possible to attract more users in the off-peak periods, but this has fiscal and financial impacts that should be considered.

Conclusions

The elasticity is a very important concept to understand the public transport users' behavior when there are fare increases. Knowing this, it is possible to have a clearer perspective of the users' reactions, and also of their possible future behaviors. The importance for the transport policy in Bogotá is that if a fare increase is made, it is possible to anticipate what will happen in the ridership. This will help decision makers to take better decisions so that the revenue is not affected too much. However, care should be taken with these increases: Although in the short term a fare increase induces a growth in revenue, this may decrease in the medium and long-term.

The econometric challenge and the originality of this research was to find a method of identifying the magnitude of TM fare elasticities given that there have been very few changes in the fares, that they take place at the same time in the whole system, and that there is a constant growing trend in ridership. The results highlight not only a negative reaction to fare increases in general but also specific features, which are related to income groups and the change of the effect in different periods along the day.

Our findings show that the introduction of fare changes exerted a negative impact on the immediate ridership for our sample observed between 2001 and 2012. The results present a fare elasticity of -0.408 in the month that follows the price change. It also show stronger reactions for the low-income population, and expect result given that the change is proportional higher for this segment of population, but an unfortunate one because the fare change is hence regressive in welfare. On average the estimated effects of integrated fares on ridership are -0.565 in the first week and -0.408 in the fourth week. Moreover, after 4 weeks the effect seems to decline but nonetheless is still present.

The results also show a reduction of the estimated elasticity as time window is increased. Our main hypothesis of this behavior is that once the fare increases, users react immediately (mainly the lower-income after a month) and change the way they travel. However, by not finding viable substitute transport modes, people return to the TM system, despite it higher cost. Users tend to adapt to the new fare, considering that TM, compared with the rest of public transport, is the most efficient transport mode for most of the population, particularly for long trips. Bogotá is a city with high population densities, low motorization rates and high congestion levels. In addition, longer waiting times and longer routes, leading unequal access to opportunities characterize the traditional public transport system (Guzman et al. 2017b). Given this knowledge of the transport system in Bogotá, it is very possible that this will happen.

Regarding policy implications, there are several an important findings: The first one is about the ridership behavior due to fare cyclic increases. This is an important to evaluate the financial effects on transport systems connected to the ridership reduction during those weeks when a demand reduction is observed. Policy fares require exhaustive analysis beyond revenue and cost-benefit analysis. Inadequate implementation of the fare policy can affect the number of passengers and reduce the likelihood of use and competitiveness of public transport systems. Any pricing policy to increase or decrease fares should be taken into account properly by local authorities, considering its effects, to offer alternatives and impact mitigation to the changes in ridership for public transport.

Another important finding is related with the continuous fare increase without a clear objective, beyond paying the private operation. The economic growth of the city during the last years has induced a strong increase of the cars and motorcycles fleet.[2] At the aggregate level, more trips are made and public transport is less attractive: Between 2000 and 2012 the fare increased 112.5%, while consumer price index was 89.1%. Complementarily, in 2012, 34% more trips were made than in 2005. However, the modal share of public transport went from 57% to 41%.

In addition, due to the widespread use of TM in Bogotá and its relatively high cost for the users compared with their income (Guzman et al. 2017b; Guzman and Oviedo 2018), the welfare impacts of the fare and its periodic increases are an important issue. Reductions in ridership following a fare increase are signs of this welfare impact on households' economy. This makes it clear that the premise of financial self-sustainability with which the Bogotá's BRT system was conceived, it is wrong. This is inconsistent with international best practices. The key elements for a competitive public transport must be its quality and accessibility, even if subsidies are required.

Decision-makers often underestimate the importance of the fare policy in public transport, as they consider that the response of users is inelastic. Although this is true in the short term, travelers adapt and in the medium and long-term and can change their transport mode. Once this happens, it is very difficult to return to use public transport regularly. The balance among fare and ridership changes should be a primary subject of analysis to prevent unwanted conditions, especially when private operators are part of the system as it is in the Bogotá scheme. These results, together with the great increase in car/motorcycle fleet and the loss of public transport share, is a warning that the authorities must take seriously. If this trend continues, the poor quality of service and the fare increases can generate an unsustainable situation, particularly for the low-income population, who suffer high

[2] Between 2002 and 2012, the car fleet increased 174%. The motorcycle fleet increased 1000% in the same period.

travel times and costs and low levels of accessibility. As a final recommendation, developing cities should implement more efficient prices that assess users' travel demands to have more efficient public transport systems. Transport subsidies to low-income population can be an interesting, equitable and progressive policy.

Further research is required in order to examine the longer-term implications of this fare increases and reductions, which is also the case in Bogotá. Between August 2012 and late 2015, the TM fare was reduced and different fare values were implemented according to the time of the day. Differential fare analysis requires an understanding of elasticity according to the change in fare conditions, including controls of socioeconomic groups, whether the fare moves up or down, and the nature of the effects of such changes in peak and off-peak hours. We will analyze fare reduction elasticity and compare the findings of this work with the situation of the reduction of fares and its effects on the substitution of demand among periods of the day. Further research is also needed to study the implications of fare changes for accessibility and equity.

Authors' contribution LAG: Manuscript writing, analysis of results, content planning and review (corresponding author). SGC: Econometric model and manuscript writing. CAMA: Analysis of results, manuscript writing and literature search.

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