# Technical efficiency of European metro systems: The effects of operational management and socioeconomic environment

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**Abstract**

This study focuses on the relationship between the operational performance of metro systems and their socioeconomic contexts. We use a two-stage methodology applied to a sample of 17 European metro systems. First, we apply a stochastic frontier approach to establish the optimal production function and to evaluate the efficiency and effectiveness levels of each firm through offer and demand-characterizing indicators, respectively. Only internal production factors are included in the first stage of this analysis. In a second stage, we use a similar modeling approach, but considering an additional set of variables characterizing the socioeconomic environment of the urban areas in which metro systems operate. This method allows observing the effects on operational performance measurements due to the inclusion of external factors, and consequently, drawing some conclusions on the technical efficiency of metro systems and their operations in beneficial or adverse surrounding environments. Different scores resulting from both perspectives evidence the contributions of the socioeconomic factors to improve the reliability of performance measurements and to reduce false inefficiencies. The results show that 12 of the analyzed systems are being affected by an unfavourable socioeconomic environment and/or their network suffers from some adequacy problems with regard to demand. The remaining 5 systems should improve their management strategies, since their results are being supported by a favourable surrounding environment.

*Keywords: metro systems; efficiency; effectiveness; internal production factors; socioeconomic environment.*

## 1. Introduction

Many public transport systems are managed by the state. State-owned firms do not usually see financial profit as their main objective; rather, they prioritize the social and environmental benefits that a rapid, reliable and eco-friendly transport system can represent in a community. Nevertheless, such systems should not disregard the improvement of their operational performance in order to become less of a burden on public finances (Dodgson 1985; Nash 2000). This has been a matter of concern across the decades for the governments, transport authorities and researchers, which have established policies and directives and developed evaluation and action tools to improve the operational performance of transport systems.

Under the scope of the Horizon 2020, the ongoing EU Framework Programme for Research and Innovation, the European Commission (EC) stresses the need for new strategic planning approaches at the local level to achieve sustainable urban mobility, since few transport authorities currently perform a reliable analysis of trends and develop scenarios to support long term policies. Therefore, the EC is promoting actions to enhance the capabilities of local authorities and other stakeholders to plan and implement sustainable mobility measures on the basis of reliable data and analysis, regarding the take-up of the innovative concept of Sustainable Urban Mobility Plans (SUMPs) at the European scale (European Commission 2014).

Our study aims to contribute to this goal, providing a tool for the analysis of the operational performance of urban rail transit systems, regarding the evaluation of production efficiency and its main drivers. We apply a stochastic frontier modeling approach to evaluate the technical efficiency of 17 European metro systems and the effects of internal and external production factors on the production. The analysis is based on historical data covering the period from 1990 to 2011, and composed of capital and labor inputs, socioeconomic indicators for the urban areas served by the systems, an output characterizing the service supply (car-kilometers), and an output reflecting the demand (number of passengers). We use a stochastic frontier regression model to process the outputs and the internal production factors, estimating the elasticities of each input. Two separate regressions are performed to establish an optimal production function for each output, from which the technical efficiency of each firm is estimated. Because we are dealing with two outputs separately, we adopt different terms for the technical efficiency. Thus, the technical efficiency associated with the supply-oriented output is simply referred to as efficiency, and is mainly dependent on the strategies applied to operational management. Similarly, the technical efficiency related to the demand characterizing output is termed effectiveness. Effectiveness reflects a transport system's capability to attract users, relying not only on the characteristics of the transport service but also on the surrounding socioeconomic environment. For this reason, a similar stochastic approach is used in a second stage to perform a regression between the set of both internal and socioeconomic indicators and the number of transported passengers. Ultimately, we are able to compare the efficiency and effectiveness levels of each firm considering the internal production factors, and also to compare the effectiveness scores with and without consideration of the external indicators.

The developed models aim to improve the knowledge on the production of European metro systems in terms of its main drivers, efficiency scores achieved by the systems, and also the extent to which the systems are operating in favorable or adverse socioeconomic contexts. Therefore, the outcomes of this study may support the development of policies and actions by the practitioners to promote sustainability in urban transit.

## 2. Literature review

The operational performance of transport networks has been studied by numerous authors; comprehensive reviews of these studies can be found in Dodgson (1985), Oum et al. (1992), De Borger et al. (2002), Brons et al. (2005), and Karlaftis (2008). In spite of many previous studies on the operational performance of bus firms (Pina and Torres 2001; Boame 2004; Odeck 2008; Sampaio et al. 2008; von Hirschhausen and Cullmann 2010; Karlaftis and Tsamboulas 2012) and long-distance railway firms (Caves et al. 1980; Tretheway et al. 1997; Cantos et al. 1999; Casson 2009; Merkert et al. 2010; Couto 2011; Wheat and Smith 2014), there has been less research on urban rail networks, and particularly on metro systems and the extent to which their productivity is affected by the internal management and socioeconomic environment, which is the scope of the current study.

Some authors have characterized public transport networks according to their topology and spatial structure. Gattuso and Miriello (2005) performed a comparative analysis of metro networks based on graph and geographic level indicators, assessing their influence on two performance indicators: commercial speed and service frequency. Nationwide transport networks were also characterized using concepts of graph theory in studies such as Erath et al. (2009), for rail and road transport, and Blumenfeld-Lieberthal (2009), for rail and air transport. Other studies have focused on the relations between the spatial structure of networks and their vulnerability and resilience under critical situations (Cats and Jenelius 2014; Jonkeren et al. 2014; Modica and

Reggiani 2014). Ducruet and Beauguitte (2013) provides a review on how the spatial approach to network analysis has evolved and integrated multidisciplinary players such as geographers, sociologists, and physicists.

Urban socioeconomic trends and their relation to the operations of transit systems have also been studied by the researchers. Babalik-Sutcliffe (2002) analyzed the two-way interactions between eight urban rail networks and their corresponding cities located in the US, Canada, and the UK. Using a set of predefined criteria, the author reported on the effects of introducing this mode of transport in the cities, as well as the external factors that enhanced or hindered systems' success since the beginning of their operations. Baum-Snow and Khan (2005) evaluated the extent to which urban rail network expansions in US cities have spurred new ridership and accounted for welfare gains in terms of commuting time savings and car ownership. The developed models incorporate potentially heterogeneous responses of public transport use to new rail infrastructure as a function of the year the system was built, distance to the city center, and physical structure of the metropolitan area as a whole. Some socioeconomic indicators, such as population density, household income, gender, age, race and schooling were used as control variables, with the first two indicators showing the most relevant influences on the location and use of rail transit systems. The authors also found that network expansions have been more successful in luring bus users than car users. Nevertheless, significant travel time savings have been induced by new rail lines. In the same vein, De Grange et al. (2012) performed an empirical evaluation of the impact of three specific policies on urban rail transit use: network expansion, fare subsidies, and regulation of private car use. The developed regression models included additional variables of control capturing socioeconomic trends. The authors found positive effects on transit ridership produced by network expansions, car use regulation, and population density. In turn, the GDP *per capita* induces a negative effect, while fare subsidies have no relevant effects on transit use. Taylor et al. (2009) analyzed the determinants of the total and *per capita* transit ridership in 265 US urban areas. This study is focused on the internal and external factors influencing the use of public transport without discerning between different modes. A two-stage regression methodology accounted for the influence of service supply on transit ridership, as well as of a wide set of policy-oriented (internal) variables and socioeconomic (external) variables. This methodology allowed overcoming the consideration of capital and labor inputs of many heterogeneous transport systems to evaluate the determinants of the overall transit ridership. The study found that service supply and transit fares are the most important factors influencing transit use. In terms of external effects, the total transit ridership is mainly affected by the population density and car ownership, while the transit ridership *per capita* mainly depends on the household income and percentage of non-transit and non-single occupancy vehicle commutes.

In terms of modelling procedures to evaluate the efficiency of urban railways and its main drivers, both parametric and non-parametric approaches were used in the existing studies. Graham et al. (2003) created a parametric model based on the Cobb-Douglas production function to estimate the elasticities of capital and labor inputs, using a cross-sectional database with 99 observations distributed by 17 networks of suburban rail and metro. These estimates were applied to the time-series data of each system to decompose the output and the productivity growth, regarding the study of scale economies. In a more recent study, Graham (2008) provides a comparison between the application of non-parametric and parametric models in the estimation of productivity and efficiency for the same modes of transport. Jain et al. (2008) used a non-parametric methodology – data envelopment analysis (DEA) – to estimate the technical and scale efficiencies of metro systems, using a 165 observation panel data sample. Only inward production factors were included in the analysis, and the results compared between public, corporatized, and private ownership systems. Tsai et al. (2014) applied a two-stage procedure using DEA and Tobit models to explore the determinants of technical, allocative and cost efficiency in 20 international urban rail systems, ranking the systems in terms of efficiency and identifying economies of scale.

The parametric approach followed in our study allows evaluating the effects of both internal and external production factors, which is the major focus of the analysis and would not be possible through a non-parametric method. In addition, technical efficiency estimates resulting from a parametric modeling approach are less sensitive to the presence of outliers.

Our study aims to contribute to the state of the art in urban transport research by conducting a production analysis exclusively developed for metro systems operating in Europe. The outcomes include tools for: (i) establishing optimal production frontiers, either for service supply or demand characterizing outputs, (ii) evaluating the effects of internal production factors and socioeconomic indicators on the production, and (iii) estimating the efficiency and effectiveness levels of each firm.

## 3. Model description

### *3.1. Background model*

We use a stochastic frontier production modeling approach to evaluate the technical efficiency of metro firms and the extent to which the socioeconomic context impacts firms' effectiveness. This approach, introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977), is a widespread concept in the econometric analysis (Coelli et al. 2005; Greene 2008) and consists of a parametric approach to evaluate a firm's efficiency in the production process, i.e., in the use of available resources (inputs) to obtain a new product or service (output). The functional form of the model is represented in Eq. (1).

$$lnY = \beta X + v - u \tag{1}$$

where $Y$ is the output produced, $X$ is the vector containing the logarithms of inputs, $\beta$ is the vector of input coefficients, $v$ is the noise term, and $u$ is the one-sided distribution error.

The model is formed by one deterministic component, $\beta X$, and two disturbance components, the one-sided distribution error and the noise term. The noise term is the random error related to the model specification or the inadvertent omission of relevant inputs and errors in data collection (Coelli et al. 2005). The probability of the noise term being favorable to production is assumed to be equal to the probability of it being unfavorable, so it takes the form of a normal and symmetric distribution, giving the random (i.e., stochastic) nature to the production frontier $exp\ (\beta X + v)$. Therefore, depending on the noise term, the stochastic frontier output can lie above or below the deterministic component $exp\ (\beta X)$. The stochastic frontier bounds the output from above, and the firms sitting below that frontier fail to achieve the ideal production rate. Thus, because the data are in log terms, the error $u$ measures the percent deviation from the stochastic frontier, i.e., the production inefficiency, being always positive and taking the form of an asymmetric distribution. The half-normal, truncated normal, exponential, and gamma distributions have been suggested as possible distributions for this error (Aigner et al. 1977; Meeusen and van den Broeck 1977; Greene 2007). The model estimation is performed using the maximum likelihood method, which is more efficient in dealing with asymmetric distribution disturbances than the least squares estimator (Greene 2008). Fig. 1 provides a graphic explanation of the stochastic production frontier approach for the cases of the stochastic frontier output sitting above (firm A) or below (firm B) the deterministic frontier.

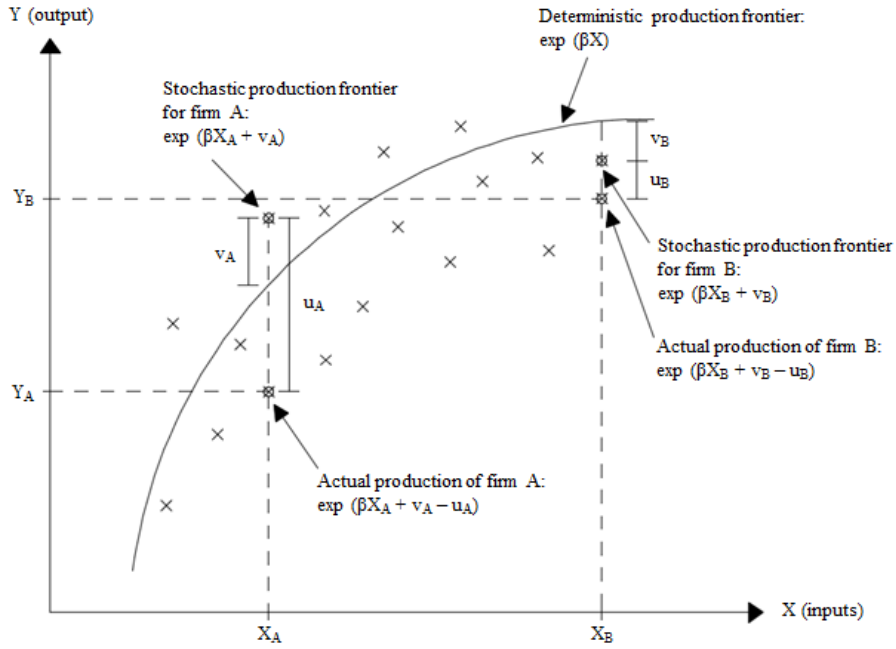


**Fig. 1** Stochastic production frontier (based on work by Coelli et al. (2005)

*3.2. Production analysis considering internal production factors*

In a first stage, we evaluate the input elasticities and technical efficiencies of metro systems. For that, we propose a stochastic production frontier based on the translog function, which is a more versatile form of the Cobb-Douglas production function, to improve the model's goodness-of-fit. Only internal production factors are included in the model, which can be written as follows:

$$lnY = lna + \sum_{i=1}^{n} b_i \, ln(INT_i) + \sum_{i=1}^{n} \sum_{j=i}^{n} c_{ij} \, ln(INT_i) ln(INT_j) + v - u \tag{2}$$

where $INT_i$ are the capital and labor inputs , $a$, $b_i$, and $c_{ij}$ are regression coefficients, and $i,j \in \{1,\ldots,n\}$.

The stochastic frontier regression in Eq. (2) is run separately for a supply-oriented output and for a demand characterizing output, allowing us to estimate the input elasticities for the observed set of metro systems, as well as the annual efficiency and effectiveness scores achieved by each system. The technical efficiency (*TE*) is given by:

$$TE = exp[-E(u \mid \varepsilon)] \tag{3}$$

where $\varepsilon$ is the composed error, such that $\varepsilon = v - u$, and $E(u|\varepsilon)$ corresponds to the mean of the conditional distribution $f(u|\varepsilon)$, estimated through the approach proposed by Jondrow et al. (1982).

*3.3. Production analysis considering internal production factors and socioeconomic indicators*

To evaluate the effects of socioeconomic context on the effectiveness of metro systems, we use a similar stochastic frontier modeling approach, but this time we account for the effects of selected socioeconomic factors that characterize the various urban areas. The resulting model is described as follows:

$$lnY = lna + \sum_{i=1}^{n} b_i \, ln(INT_i) + \sum_{i=1}^{n} \sum_{j=i}^{n} c_{ij} \, ln(INT_i) ln(INT_j) + \sum_{k=1}^{p} d_k \, ln(EXT_k) + v - u \tag{4}$$

where $EXT_k$ are the observed external factors, $d_k$ are regression coefficients, and $k \in \{1,\ldots,p\}$.

In this stage, the model is exclusively applied to the demand characterizing output, which is the most sensitive to the socioeconomic changes. The effectiveness is then recalculated using Eq. (3), which allows comparing between the results of both stochastic models (Eq. (2) and (4)) and drawing some conclusions about the favorable or unfavorable effects of socioeconomic factors on metro systems' operational performance.

## 4. Model application

*4.1. Data collection*

The first step for the application of the stochastic frontier modeling approach described in section 3 was to build a database covering the main indicators on the operation of European metro systems, as well as some socioeconomic features with potential influence on the demand for public transport in urban areas. Hence, we collected the input and output data from annual reports and/or other official information released by metro firms or transport authorities. The socioeconomic factors were assessed in the Urban Audit database (Eurostat, 2013). Our final database included 17 European metro systems operating in the period from 1990 to 2011. The selected systems are: Barcelona (TMB), Berlin (BVG), Brussels (STIB), Budapest (BKV), Glasgow (SPT), Hamburg (HVV), Helsinki (HKL), Lisbon (ML), London (TfL), Madrid (MM), Milan (ATM), Munich (MVG), Paris (RATP), Porto (MP), Prague (DPP), Rome (ATAC), and Turin (GTT).[1] Although the Porto and Turin metros use light rail vehicles, they have rights-of-way separated from the road traffic, and so are included in this analysis.

We consider the following internal inputs in this study: network length (*NL*), the number of stations (*NS*), the number of cars (*NC*), and the number of employees (*NE*).[2] *NL*, *NS*, and *NC* characterize the firms' capital,

[1] Other metro systems were initially considered but subsequently discarded from the database due to inconsistent and/or missing data.

[2] For some companies operating the metro and other transit systems, the published number of employees refers to the total labor force. In

while *NE* represents the labor force. We found scarce information on materials and energy consumption. Therefore, we do not consider such indicators for this application. Nevertheless, it is expected that firm consumptions be proportional to their capital; hence, we assume that the effects of consumptions may be captured by the capital variables.

As mentioned in section 1, we perform two measurements of technical efficiency using different outputs: the number of car-kilometers produced (*CRKM*) for efficiency estimation, and the number of transported passengers (*PASS*) for effectiveness estimation. Because output data were not available for the entire period under consideration, the car-kilometers panel data have 167 observations and the passengers panel data have 186 observations. In Table 1, we present the generic features of the observed metro systems.

**Table 1** Internal inputs and outputs (mean values)

| System | Internal inputs | | | | | Outputs | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Period | NL (km) | NS | NC | NE | Period | CRKM (millions) | Period | PASS (millions) |
| Barcelona | 1999-2011 | 88 | 112 | 665 | 3,091 | 1999-2011 | 70.2 | 1999-2011 | 342.8 |
| Berlin | 2002-2011 | 145 | 171 | 1,326 | 4,927 | 2002-2007 | 125.6 | 2006-2011 | 482.7 |
| Brussels | 2003-2011 | 48 | 64 | 253 | 1,274 | 2005-2006 | 11.5 | 2003-2011 | 124.3 |
| Budapest | 1996-2011 | 31 | 40 | 394 | 1,752 | 1996-2003 and 2008-2010 | 30.1 | 1996-2011 | 296.8 |
| Glasgow | 1997-1998 | 10 | 15 | 41 | 326 | 1997-1998 | 3.4 | 1997-1998 | 14.4 |
| Hamburg | 2003-2011 | 101 | 89 | 764 | 3,087 | 2003-2011 | 75.8 | 2003-2011 | 187.0 |
| Helsinki | 2001-2011 | 21 | 16 | 108 | 216 | — | — | 2001-2011 | 56.5 |
| Lisbon | 1993-2011 | 30 | 38 | 293 | 1,806 | 1993-2011 | 18.7 | 1993-2011 | 164.7 |
| London | 1994-1998, 2002-2006, and 2010-2011 | 421 | 292 | 4,034 | 15,185 | 1994-1998, 2002-2006, and 2010-2011 | 465.0 | 1994-1998, 2002-2006, and 2010-2011 | 949.2 |
| Madrid | 1997-1998 and 2000-2011 | 222 | 235 | 1,736 | 5,993 | 1997-1998 and 2000-2010 | 150.4 | 1997-1998 and 2000-2011 | 592.7 |
| Milan | 1990-2005 | 69 | 79 | 705 | 2,914 | 1990-2005 | 51.4 | 1990-2005 | 302.7 |
| Munich | 2003-2011 | 91 | 94 | 583 | 2,475 | 2003-2011 | 61.4 | 2004-2011 | 340.6 |
| Paris | 1992-2011 | 212 | 297 | 3,510 | 11,971 | 1992-2011 | 216.8 | 1992-2011 | 1,282.1 |
| Porto | 2003-2011 | 48 | 58 | 186 | 371 | 2003-2011 | 15.4 | 2003-2011 | 37.2 |
| Prague | 2002-2011 | 56 | 53 | 710 | 2,678 | 2002-2011 | 47.5 | 2002-2011 | 524.6 |
| Rome | 2001-2011 | 37 | 48 | 466 | 2,566 | 2001-2011 | 33.5 | 2001-2011 | 300.3 |
| Turin | 2006 and 2008-2011 | 10 | 15 | 103 | 153 | 2006 and 2008-2011 | 8.1 | 2006 | 9.0 |

To characterize the urban areas, we consider the following variables: area (*AREA*), population density of the core city (*PDCC*), average household size (*AHS*), unemployment rate (*UR*), gross domestic product *per capita* (*GDP*), and diesel pump price (*DPP*).[3] These indicators were collected for the Larger Urban Zones (LUZ), except *PDCC*, which was collected for the core city due to data availability. The concept of LUZ defines functional urban zones surrounding the core cities, and both territorial units allow for comparable measurements on different characteristics of the Urban Audit cities. The mean values of the socioeconomic factors for the periods considered for each urban area are presented in Table 2.

these cases, aiming to remove the number of employees associated with other transport modes, we estimated *NE* through a linear regression between the labor force and the metro rolling stock, using specific dummy variables for each company.

[3] *GDP* and *DPP* were converted at 2000 constant prices.

**Table 2** Socioeconomic characteristics of the urban areas (mean values)

| System | Period | Socioeconomic factors | | | | | |
|---|---|---|---|---|---|---|---|
| | | AREA ($km^2$) | PDCC (inh./$km^2$) | AHS (inh./household) | UR (%) | GDP (EUR/inh.) | DPP (EUR) |
| Barcelona | 1999-2011 | 1,797 | 15,973 | 2.9 | 11.3 | 19,841 | 0.72 |
| Berlin | 2006-2011 | 17,385 | 3,854 | 1.8 | 13.5 | 22,502 | 1.11 |
| Brussels | 2003-2011 | 1,620 | 6,434 | 2.3 | 15.4 | 32,889 | 0.89 |
| Budapest | 1996-2011 | 2,542 | 3,354 | 2.4 | 5.3 | 11,138 | 0.72 |
| Glasgow | 1997-1998 | 3,346 | 3,376 | 2.2 | 12.6 | 27,101 | 0.98 |
| Hamburg | 2003-2011 | 7,304 | 2,331 | 2.0 | 7.3 | 34,155 | 1.04 |
| Helsinki | 2001-2011 | 2,970 | 3,054 | 2.1 | 7.2 | 38,783 | 0.92 |
| Lisbon | 1993-2011 | 1,433 | 6,571 | 2.6 | 9.0 | 16,668 | 0.73 |
| London | 1994-1998, 2002-2006, and 2010-2011 | 8,920 | 4,645 | 2.4 | 7.3 | 32,427 | 1.02 |
| Madrid | 1997-1998 and 2000-2011 | 8,023 | 5,105 | 2.9 | 15.9 | 21,747 | 0.71 |
| Milan | 1990-2005 | 1,608 | 7,138 | 2.4 | 6.0 | 26,724 | 0.84 |
| Munich | 2004-2011 | 5,529 | 4,219 | 1.9 | 4.8 | 35,414 | 1.07 |
| Paris | 1992-2011 | 12,080 | 20,469 | 2.4 | 11.7 | 36,814 | 0.80 |
| Porto | 2003-2011 | 562 | 5,408 | 2.8 | 15.0 | 12,977 | 0.86 |
| Prague | 2002-2011 | 6,982 | 2,439 | 2.4 | 4.1 | 15,340 | 0.87 |
| Rome | 2001-2011 | 3,667 | 2,033 | 2.4 | 8.6 | 23,882 | 0.93 |
| Turin | 2006 | 1,879 | 6,833 | 2.2 | 5.3 | 19,018 | 0.99 |

We also consider the presence of other urban rail transit systems in the same urban area as an external factor, using the dummy variable *OUR*. This variable reflects the existence of tramways, light rail or metro-like systems,[4] being set to 1 if one or more of these systems exist or to 0 otherwise. The variable *OUR* aims to provide some information on the complementary or competitive relationship between systems. Because bus and commuter rail networks are present in all of the analyzed cities, dummy variables for these transport modes are not considered.

### *4.2. Estimating input elasticities, efficiency and effectiveness*

Using the stochastic frontier regression in Eq. (2), we developed two individual models for the outputs car-kilometers (*CRKM* model) and number of passengers (*PASS* model A).[5] We divided the capital and labor inputs by the network extension due to the great variability in the dimension of the metro systems under consideration, ranging from almost 10 km in Glasgow to more than 400 km in London. The mean values of the first order factors were transformed into a value of 0 in order to compare their mean elasticities. We included a time trend variable *YR* aiming to capture the effect of gaining production expertise throughout time. In the modeling process, we considered that the error *u* assumes an exponential distribution, and we followed a stepwise approach. First, we calibrated both models including only the first order factors. Then, to avoid possible multicollinearity issues that may affect the parameter estimates, the second order factors were gradually introduced in the models until a good solution was obtained, according to two criteria: (i) the estimates of the first order factors should reflect a plausible interpretation and should not vary significantly from the original estimates, and (ii) the models should include as much second order factors as possible without compromising the previous criterion. Therefore, only four second order factors – *NL.NC*, *NL.NE*, *NS.NC*, and *NS.NE* – were included in the final models, presenting correlations with the first order factors of around 0.6 in two cases and less than 0.3 in the remaining cases. The variables *NL.NS*, *NC.NE*, $NL^2$, $NS^2$, $NC^2$, and $NE^2$ were dropped from this analysis. We opted to provide both *CRKM* model and *PASS* model A with similar specifications, maintaining the variable *NS.NC* in the latter model despite its lack of statistical significance at the 10% level ($P[|Z|>z] = 0.256$). The modeling results are presented in Table 3.

[4] By metro-like systems we intend urban rail systems which combine features of metro and commuter rail notwithstanding the existence of these latter systems in the same urban area (e.g. the RER in Paris is a suburban rail that operates similarly to a metro system within the core city limits, coexisting with the RATP metro and the SNCF Transilien commuter rail service).

[5] Modeling estimations were performed using the econometric software *Limdep* (Greene 2007).

**Table 3** Results of the stochastic frontier models considering internal production factors

| Variable | CRKM model | | | PASS model A | | |
|---|---|---|---|---|---|---|
| | Coefficient | Standard error | P[\|Z\|>z] | Coefficient | Standard error | P[\|Z\|>z] |
| Constant | 10.984 | 0.033 | 0.000 | 12.538 | 0.056 | 0.000 |
| YR | 0.007 | 0.002 | 0.000 | 0.021 | 0.003 | 0.000 |
| NL | 1.127 | 0.015 | 0.000 | 0.809 | 0.026 | 0.000 |
| NS | -0.209 | 0.063 | 0.001 | -0.279 | 0.137 | 0.042 |
| NC | 0.233 | 0.062 | 0.000 | 0.621 | 0.075 | 0.000 |
| NE | 0.410 | 0.047 | 0.000 | 0.760 | 0.072 | 0.000 |
| NL.NC | -0.396 | 0.050 | 0.000 | -0.519 | 0.069 | 0.000 |
| NL.NE | 0.411 | 0.064 | 0.000 | 0.262 | 0.058 | 0.000 |
| NS.NC | -0.965 | 0.379 | 0.011 | -0.435 | 0.383 | 0.256 |
| NS.NE | 0.883 | 0.443 | 0.046 | 0.840 | 0.305 | 0.006 |
| | No. of observations = 167 | | | No. of observations = 186 | | |
| | Log-likelihood = 133.929 | | | Log-likelihood = 10.689 | | |
| | $\sigma_u = 0.089$ | | | $\sigma_u = 0.284$ | | |
| | $\sigma_v = 0.072$ | | | $\sigma_v = 0.067$ | | |

From the analysis of Table 3 we can draw some conclusions about each input's influence on the final outputs. The coefficient of *YR* reveals that the passing of time slightly increases output production, reflecting positive technological changes. Even if all production resources hold constant, firms tend to produce more by improving their expertise in the production process.

Because all capital and labor inputs were divided by *NL*, the elasticity of *NL* is given by $b_{NL} - (b_{NS} + b_{NC} + b_{NE})$, i.e., 0.693 in the *CRKM* model and -0.294 in the *PASS* model A. An increase in *NL*, holding the remaining factors constant, represents a theoretical scenario in which the same rolling stock would be operating in a larger network, thus increasing the output *CRKM*. However, because the frequency would be lower, the system would become less attractive to users, which is reflected by the decrease in the output *PASS*. Future network expansions should be carefully considered to avoid oversized metro systems that may negatively impact their production.

Increasing *NS* has negative effects on both service supply and demand (elasticities of -0.209 and-0.279, respectively), probably because it would imply more stops, and consequently less fluidity in the system and a greater difficulty in adjusting the train schedules. In other words, despite the potential increase in the population served by metro systems, the introduction of new stations can affect their production because passengers may opt for other transport services, especially in longer journeys, due to the increase in the metro travel time and the decrease in the service frequency.

The elasticity values of *NC* (0.233 for *CRKM* and 0.621 for *PASS*) indicate that increasing the rolling stock raises the production. In this sense, a greater number of cars would allow firms to put more trains on the tracks and/or to use longer trains, thus increasing *CRKM*. Also, by reducing users' waiting time and by offering more space and comfort on board, metro systems become more appealing to the public.

Because we are dealing with production, and the results of a cost analysis would eventually be different, an increase in *NE* has a positive effect on the figures of *CRKM* and *PASS* (elasticities of 0.410 and 0.760, respectively). In addition, users may be more attracted to more humanized systems, which generally achieve better results in areas such as security and user support.

At this stage we were also able to estimate the technical efficiency for each observation using Eq. (3). The graph in Fig. 2 presents the comparison between the average scores of production efficiency and effectiveness for each system, considering the available observations in the period from 2002 to 2011.[6] [7]

[6] The results for the Glasgow metro correspond to the operational years of 1997 and 1998 (the only available data).

[7] The Helsinki metro is not represented in Fig. 2 because its efficiency was not estimated due to the lack of data about *CRKM*.

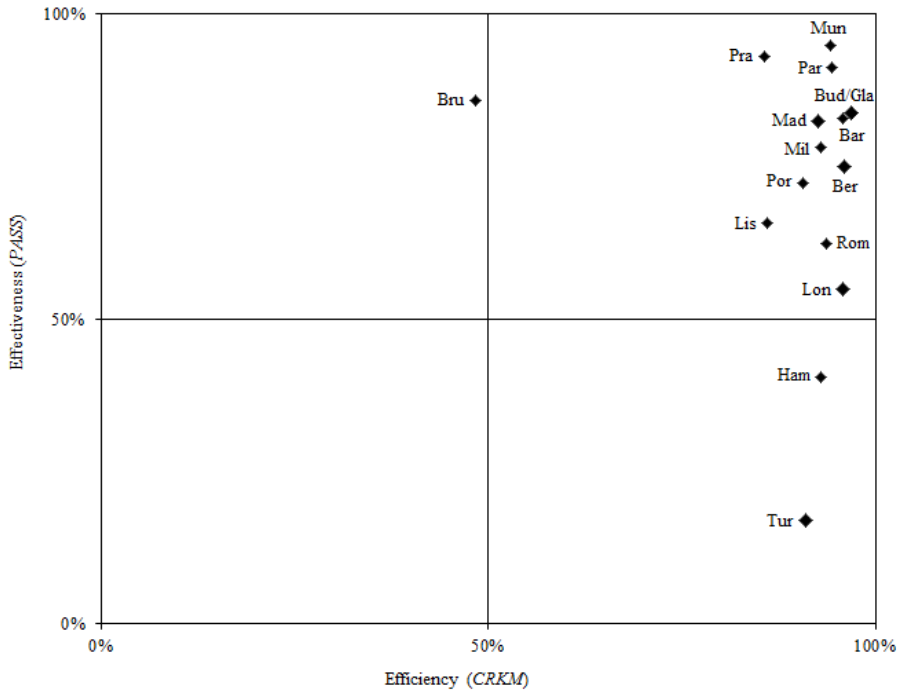


**Fig. 2** Efficiency and effectiveness scores

We divided the graph in Fig. 2 into quadrants to simplify the comparisons among metro systems. It is possible to observe that the great majority of the systems fall in the first quadrant, showing efficiency and effectiveness scores greater than 50%. These results reflect good trade-offs between operational management and attractiveness to the general public. With a 94% efficiency score and a 95% effectiveness score, the Munich metro achieves the best trade-off between both technical efficiency measures. This system, together with the systems of Helsinki,[7] Paris, and Prague are the most effective in attracting users, sitting above the 90% barrier. In terms of efficiency results, Fig. 2 shows a rather satisfactory panorama, denoting an adoption of good operational management strategies by European metro firms, with 13 out of 16 systems scoring above 90%. These systems are Barcelona, Berlin, Budapest, Glasgow, Hamburg, London, Madrid, Milan, Munich, Paris, Porto, Rome, and Turin. The average efficiency and effectiveness scores for the studied metro systems are of 90% and 74%, respectively.

The Brussels metro (efficiency of 48% and effectiveness of 86%) is placed in the second quadrant. Despite being attractive to the public, the system needs an improvement in operational management strategies in order to bring its efficiency to the average level of the industry. The Turin metro (efficiency of 91% and effectiveness of 17%) and the Hamburg metro (efficiency of 93% and effectiveness of 41%) are located in the fourth quadrant, revealing that a good service supply has not been accompanied by the capture of passengers. Generically, systems in this quadrant may be facing an inadequate network size or design, or an unfavorable socioeconomic context. While network reconfigurations are difficult to implement in the short term and the evolution of the external environment is frequently uncertain, firms may try to attract more passengers by adopting policies such as increasing advertising investment or improving the safety and cleanliness of trains and stations. However, in the particular case of the Turin metro, the low effectiveness score may be related to the fact that it reports only to the opening year (2006), when citizens were still adapting their daily routines to the introduction of the new transport system. No data on the number of transported passengers were available for the following operational years.

In this study, efficiency scores vary from 48% to 97% and effectiveness scores from 17% to 95%, denoting that the technical efficiency of urban transport systems may vary widely. However, the systems of Brussels and Turin may be regarded as outliers in relation to efficiency and effectiveness, respectively. Without considering these systems, efficiency varies from 86% to 97% and effectiveness from 41% to 95% within the sample of metro systems. The results obtained are consistent with those from previous research. Great variations in the technical efficiency of urban transit systems were reported in the review study by De Borger et al. (2002), where diverse authors' results vary from 24% to 100%. That study highlights the results obtained by Gathon (1989), who performed a parametric frontier model (translog production function) and found technical

efficiencies between 58% and 100%. In terms of the adoption of non-parametric methods, Wunsch (1994; 1996) found average technical efficiencies between 43% and 100%, using a free disposal hull (FDH) model, and between 26% and 100% using a DEA model for urban bus and rail transport systems. Other applications of DEA models to measure the performance of urban rail systems have been performed in studies such as Jain et al. (2008), with technical efficiencies ranging from 35% to 100%, and Tsai et al. (2014), in which efficiency scores were corrected by a bootstrapping procedure, varying from 43% to 88%.

*4.3. Evaluating the impacts of the socioeconomic factors*

The stochastic frontier regression in Eq. (4) allowed us to develop a new model for the output number of passengers (*PASS* model B), including the first and second order variables considered in *PASS* model A presented in Table 3 and the socioeconomic factors described in Table 2. The maximum correlation coefficient between variables from the previous models was not affected by the introduction of the external factors. Once again, we considered an exponential distribution for the error *u*. The results are shown in Table 4.

**Table 4** Results of stochastic frontier model considering internal production factors and socioeconomic indicators

| Variable | PASS model B | | |
|---|---|---|---|
| | Coefficient | Standard error | P[\|Z\|>z] |
| Constant | 4.433 | 0.011 | 0.000 |
| YR | 0.006 | 0.000 | 0.000 |
| NL | 0.241 | 0.001 | 0.000 |
| NS | -0.312 | 0.002 | 0.000 |
| NC | 0.986 | 0.001 | 0.000 |
| NE | 0.040 | 0.001 | 0.000 |
| NL.NC | -0.668 | 0.001 | 0.000 |
| NL.NE | -0.008 | 0.001 | 0.000 |
| NS.NC | -1.501 | 0.007 | 0.000 |
| NS.NE | 0.062 | 0.005 | 0.000 |
| AREA | 0.441 | 0.000 | 0.000 |
| PDCC | 0.445 | 0.000 | 0.000 |
| AHS | 0.042 | 0.002 | 0.000 |
| UR | -0.087 | 0.001 | 0.000 |
| GDP | 0.067 | 0.001 | 0.000 |
| DPP | 0.103 | 0.001 | 0.000 |
| OUR | -0.032 | 0.000 | 0.000 |
| | No. of observations = 186 | | |
| | Log-likelihood = 114.017 | | |
| | $\sigma_u = 0.197$ | | |
| | $\sigma_v = 1\times10^{-5}$ | | |

In *PASS* model B, the variance of the noise term *v* decreases to an almost null value in comparison to *PASS* model A (see Table 3). Therefore, the random effects among observations are being captured by the external factors, meaning that the optimal production function is defined by an almost deterministic frontier. From *PASS* model A to *PASS* model B, the introduction of the external factors affects the elasticities of the internal production factors in terms of magnitude, but not in terms of sign, and for this reason, we will only comment the results in Table 4 related to the effects of the external factors on the output production.

The positive coefficient of the variable *AREA* reflects that operating in more extensive urban areas tends to increase the output production. In fact, larger metropolitan areas generally include a wider set of suburban and satellite cities that have strong socioeconomic relationships with the core city, representing a greater number of multimodal commuters and potential users of metro systems. However, metro networks should not cover all the satellite cities if it implies crossing less populated areas, leaving that purpose for the commuter rail; the positive impact of the variable *PDCC* on the output production strengthens the benefits of metro systems covering the most highly populated areas. These results are consistent with other studies such as Baum-Snow and Khan (2005), Taylor et al. (2009), and De Grange et al. (2012). The increase of *AHS*, holding the remaining factors constant, increases the number of passengers using the metro. Large households have a traditionally higher ratio of non-drivers (e.g., children), and even some of the drivers tend to share the same car, reducing the car availability for the use of a single person. Then, mobility needs may be fulfilled by public transport. The unemployment growth affects the metro production because as more people lose their jobs, less commuting trips are taken per day. The growth of the GDP *per capita* has a positive effect on metro production. This result is consistent with the findings of Baum-Snow and Khan (2005) and Taylor et al. (2009), but an opposite effect was reported by De Grange et al. (2012). The GDP *per capita* reflects the population income and the wealth of an

urban area, thus we believe that its growth denotes a more prosperous economic environment which intensifies mobility needs. Also in this scenario, transport firms have more financial resources to invest in the upgrade of their productive process. The positive coefficient of *DPP* confirms that increases in fuel prices may persuade private car users to change their traveling behavior and shift to public transport. The existence of trams, light rails, or other metro systems operating in the same urban area slightly decreases the production of the main metro system (negative coefficient of *OUR*). The competition between multiple systems seems to prevail over the perspective of an intermodal complementarity that would enhance the public transport productivity. This result suggests that additional efforts should be made to promote integrated strategies of network planning and management involving all modes of urban public transport, avoiding route overlapping and defining the most adequate service for each zone.

In terms of the effectiveness levels, the scores from the application of *PASS* model B (internal and external factors) were estimated using Eq. (3), and are shown in Fig. 3 along with the scores from the application of *PASS* model A (internal factors).

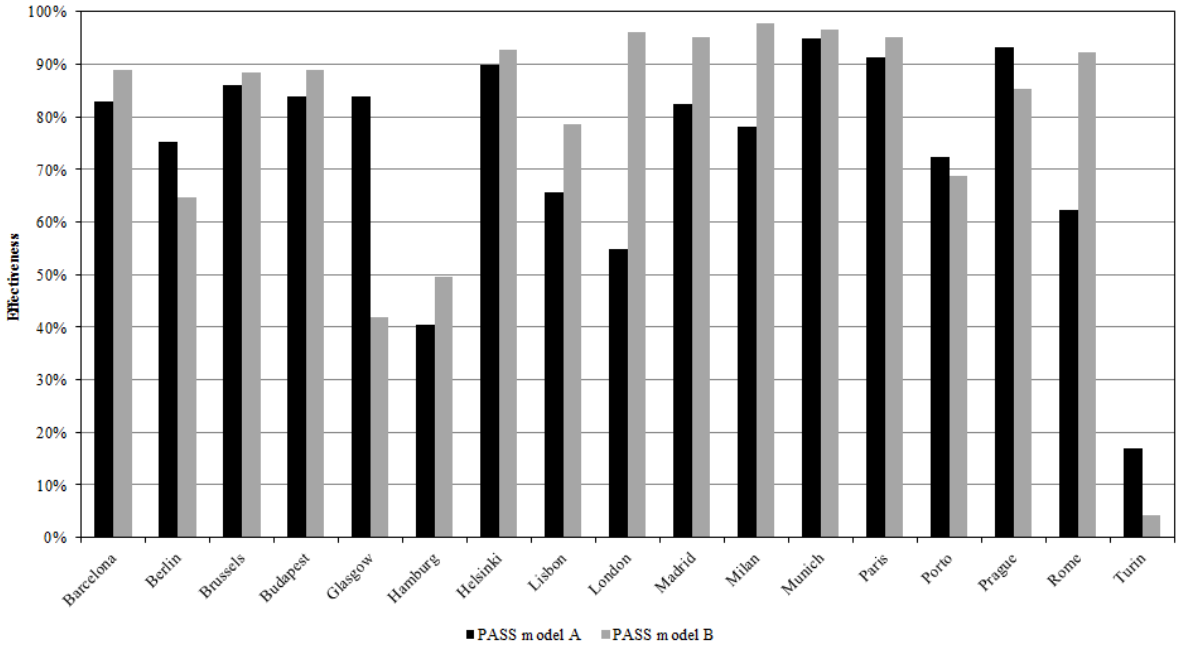


**Fig. 3** Effectiveness scores from *PASS* model A and *PASS* model B

In Fig. 3 we can see that the inclusion of the socioeconomic indicators in *PASS* model B produces some variations in the effectiveness scores of metro systems, confirming the influence of external factors on the technical efficiency of the productive process. Compared to *PASS* model A, the application of *PASS* model B results in an increase in the effectiveness scores of 12 metro systems: Barcelona, Brussels, Budapest, Hamburg, Helsinki, Lisbon, London, Madrid, Milan, Munich, Paris, and Rome. This fact indicates that the higher inefficiencies returned by *PASS* model A account not only for faults in management policies but also for some inadequacies of metro systems with regard to demand. Possible causes for these inadequacies include the network size and configuration (usually defined by politics), socioeconomic turnarounds, and even cultural influences on the modal choice. In other words, the effectiveness scores obtained with *PASS* model A are penalized by unfavorable surrounding environments that are not the firms' responsibility. The Turin metro reveals the greatest effectiveness variation, which is consistent with the fact that the results correspond to its opening year, reflecting a small network and a non-consolidated demand for metro service.

In an opposite scenario, the remaining 5 metro systems – Berlin, Glasgow, Porto, Prague, and Turin – have a decrease in their effectiveness scores due to the application of *PASS* model B. In these cases, the effectiveness scores returned by *PASS* model A benefit from favorable surrounding environments. Still, these systems should seek to improve their operational management.

## 5. Conclusions

In this study, we perform an analysis of the operational performance of metro systems, using a database containing 17 networks in Europe. Because we intended to estimate both input elasticities and effectiveness scores, we opted for a parametric approach. Therefore, we used a stochastic frontier regression based in the translog production function to estimate the elasticities of capital and labor inputs and the technical efficiency achieved by each firm in the production processes of a supply-oriented output (car-kilometers) and of a demand characterizing output (passengers), obtaining an estimation model for each output (*CRKM* model and *PASS* model A). Afterwards, we reassessed the firms' effectiveness scores by including a set of selected socioeconomic indicators in the stochastic frontier regression modeling, considering only the output related to the number of passengers (*PASS* model B).

The results confirm the importance of both internal and external production factors on the output production of metro systems. The effects of the internal production factors are consistent between *PASS* models A and B, varying in magnitude due to the consideration of external factors, but maintaining the trends of benefiting or harming the production numbers. The effects of increasing each internal and external factor on the production of each output are summarized in Table 5.

**Table 5** Positive and negative effects/elasticities in the production process of the analyzed metro systems

| Production factors | Outputs | | | |
|---|---|---|---|---|
| | Car-kilometers | | Passengers | |
| | Positive effects | Negative Effects | Positive effects | Negative Effects |
| Internal production factors | Passing of time<br>Network length<br>Number of cars<br>Number of employees | Number of stations | Passing of time<br>Number of cars<br>Number of employees | Network length<br>Number of stations |
| Socioeconomic indicators | | | Area<br>Population density<br>Average household size<br>GDP *per capita*<br>Diesel pump price | Unemployment rate<br>Other urban rail systems |

With regards to the levels of efficiency estimated by the *CRKM* model, we may assume that most of the systems have a good operational performance, with 13 systems presenting levels above 90%: Barcelona, Berlin, Budapest, Glasgow, Hamburg, London, Madrid, Milan, Munich, Paris, Porto, Rome, and Turin. In turn, effectiveness estimations given by the *PASS* model A revealed 4 systems standing out with effectiveness scores greater than 90%: Helsinki, Munich, Paris, and Prague. The Munich metro achieves the best trade-off between efficiency and effectiveness, while Brussels has the least efficient system and Turin has the least effective system. Because the effectiveness is directly dependent on the travel demand, the average effectiveness observed is smaller than the average efficiency (74% *versus* 90%).

The variations in the effectiveness from *PASS* model A to *PASS* model B show the relevance of the external factors on the performance of urban rail and reveal the extent to which such factors may help improve the reliability of the performance figures by reducing false inefficiencies. Systems whose scores increase due to the inclusion of the external factors on the deterministic component of the production function are being affected by an unfavorable socioeconomic environment, being the case of Barcelona, Brussels, Budapest, Hamburg, Helsinki, Lisbon, London, Madrid, Milan, Munich, Paris, and Rome. Although network reconfigurations may be planned to improve the systems' adequacies based on their urban environments, they can only be implemented in the long term, particularly if input cuts are involved. In this case, opposition may be raised by the workers who fear losing their jobs, as well as by the community, which is concerned with potential reductions in the quality and quantity of the transport service. Nevertheless, some policies to increase users' attraction and satisfaction, such as developing good advertising campaigns and promoting a clean and secure environment in trains and stations, are easier for metro firms to implement in the short term. On the other hand, systems presenting a decrease in their effectiveness scores have an opportunity to improve their input management, since their operational results are being helped by a favorable surrounding environment. This is the case of Berlin, Glasgow, Porto, Prague, and Turin.

This study aims to contribute to the state of the art of urban rail transport research by conducting an analysis on the determinants of the production of metro systems. Improved knowledge on the main internal and external factors affecting firms' production will help the practitioners tackle the causes of inefficiency of existing systems and adopt good practices at the planning stage of new metro networks or expansions. The outcomes of this study may be used as tools for reliable trend analyses and predictions related to urban rail transport

production, promoting the development and implementation of sustainable mobility policies and actions, particularly in the long term.

Further research on the development of decision-supporting tools to enhance the capabilities of local authorities and other stakeholders to improve the efficiency of all modes of urban transport and mitigate the negative effects of inefficiencies is planned in the near future. Such approach requires a strong engagement among researchers and practitioners; the envisioned tools should allow stakeholders to prioritize their objectives according to the specific transport-related challenges faced by each urban area, and should be flexible enough to support the implementation of a wide range of sustainable mobility measures, including newly-emerging technologies, low-emission vehicles, alternative transport modes (e.g., car-sharing, cycling, walking), changes to network configuration, and policy-based measures. The methodologies undertaken should result in solid instruments to assist local authorities in defining quantified targets to prepare and implement SUMPs, meeting the most recent European directives.

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