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Efficiencies of the urban railway lines incorporating financial performance and in-vehicle congestion in the Tokyo Metropolitan Area

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ABSTRACT

This study reviews the operations in 18 lines of seven major urban railway operators in the Tokyo Metropolitan Area and empirically evaluates their efficiencies while incorporating financial performance and in-vehicle congestion. The data were collected from statistical sources publicly available in Japan, and they contain in-vehicle congestion rates, line lengths, number of stations, vehicle kilometers, number of passengers, passenger kilometers, operating revenues by railway line, and operating expenses by operator in 2017. The line-level efficiencies of the operational efficiency, cost efficiency, and revenue efficiency were analyzed using data envelopment analyses, and Tobit regression was applied to examine how in-vehicle congestion rates are associated with these efficiencies. The efficiency analysis results showed that incorporating the in-vehicle congestion rate into operational efficiency enables to reflect the quality-of-service of the railway operation into the efficiency scores. Moreover, higher in-vehicle congestion rate leads to a lower cost efficiency but a higher revenue efficiency. The possible measures to improve efficiencies were discussed as per the categories of lines.

1. Introduction

Urban railways play a vital role in passenger transportation in many major cities, and they usually provide efficient services with high network density quality and reliability. This is also the case in the Tokyo Metropolitan Area (TMA) of Japan. However, in the TMA, transportation capacity shortages and high in-vehicle congestion have been existing during peak hours for many years (Ieda et al., 2001). In 2019, the average in-vehicle congestion rate during peak hours on 31 major lines in the TMA was 163%, which is higher than the 150% targeted by the Government of Japan (Ministry of Land, Infrastructure, Transport and Tourism (MLIT), Japan, 2018). Although there is a social requirement to alleviate in-vehicle congestion, capital investments in improving the existing lines, such as by upgrading rail lines into quadruple tracks, increasing passenger cars, and expanding station platforms, have not been sufficiently conducted due to the sluggish demand growth caused by the population decline in recent years. Besides, since the elasticity of demand with respect to service and price is small due to the local monopolistic feature of railway transportation in the TMA, the concerned railway companies do not expect a significant increase in profits from costly capital investments (Okamura, 1997). In-vehicle congestion enhances the profitability of urban railway operators; however, it worsens the service level for railway passengers. Although many local stakeholders, including railway passengers, request railway operators to invest in reducing in-vehicle congestion, the additional capital investments under the declining transportation demand will possibly lead to a deterioration in the financial performance of railway operators. Many researchers have pointed out the underinvestment problem in Tokyo under the principle of profit maximization of private companies (Okamura, 1997; Ieda et al., 2001).

The Government may also expect railway companies to increase the capacity of urban railways because it assumes that railway companies earn sufficient profits with congested railway lines. Some railway companies successfully make adequate profits from congested lines, but others do not. Fig. 1 shows the financial performance against the in-vehicle congestion rates of 18 urban railway lines in the TMA. Although all the railway lines have good financial performance with an operating revenue/expenses ratio of more than 100%, the in-vehicle congestion rates significantly vary across the lines. As shown in the figure, most of the railway lines suffer from high in-vehicle congestion rates that are over the target rate set by the Government (150%). For example, some railway lines, such as the Tozai line, which is operated by

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the Tokyo Metro Co. (a public-owned railway company), have very high congestion rates but relatively poor financial performance. In contrast, the Isesaki line, which is operated by Tobu Railway Co. (a private railway operator), has a low congestion rate and the highest operating revenue/expense ratio. The railway companies with small profits may not be able to invest in reducing in-vehicle congestion. The figure also indicates that some railways with similar financial performance levels have different congestion rates, such as the Denentoshi and Keio lines. However, there are lines with similar congestion rates but with different financial performance levels, such as the Odawara, Inokashira, and Isesaki lines. So, why are there business performance differences across railway companies even with similar in-vehicle congestion rates?

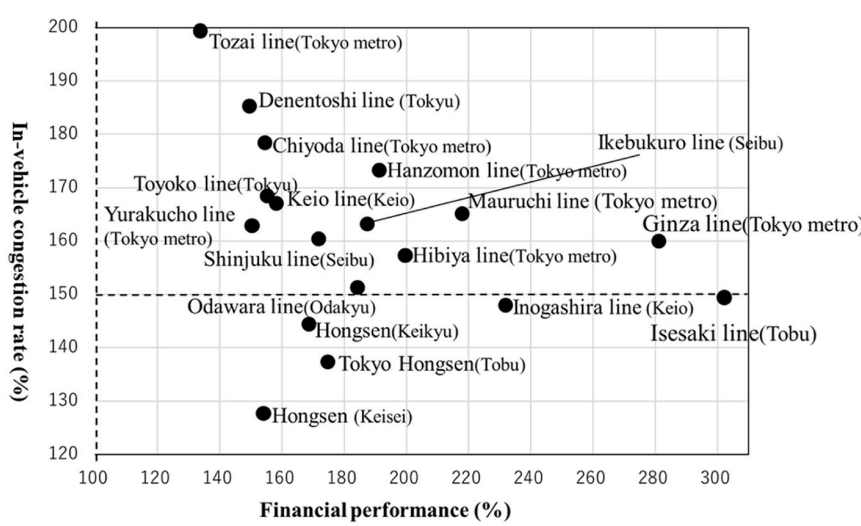
Some railway operators have made efforts to improve operational efficiency, reduce operating expenses, and enhance operating revenue to achieve good financial performance while maintaining low in-vehicle congestion rates. Nevertheless, in-vehicle congestion has been rarely considered in the empirical studies on railway operation efficiency or the financial performance of railway operators. Thus, this study aims to review the operations of the major railway operators in the TMA and to empirically evaluate their efficiencies while incorporating in-vehicle congestion. Three types of efficiencies were analyzed in the 18 urban railway lines in an attempt to identify the factors that account for differences in the financial performance of railway operators and in-vehicle congestion.

In this study, the traditional data envelopment analysis (DEA) was adopted to evaluate the line-level efficiency of the major railways in the TMA. There are many efficiency analysis approaches for estimating the efficiency of railways, including the total factor productivity method used by Nakajima and Fukui (1996), the stochastic frontier analysis applied in the efficiency analyses of European railways (Gathon and Pestieau, 1995), nonparametric frontier methods of DEA proposed by Oum and Yu (1994) for measuring the productive efficiency of railway systems in 19 OECD countries, and other numerous studies that applied improved DEA to efficiently analyze the railway sector. This study does not propose a new method for evaluating railway performance, but it aims to empirically add the aspects of in-vehicle congestion to the existing factors related to railway performance. In particular, three performance indicators were proposed for evaluating the performance of railway lines: operational efficiency, cost efficiency, and revenue efficiency. It is expected that an efficiency analysis of Japanese railway lines that incorporates financial performance and in-vehicle congestion can provide implications for developing a public transit strategy not only from the viewpoint of railway operators but also from that of society, including railway users.

The rest of this paper is organized as follows. Section 2 reviews the existing literature that applied DEA to analyze the efficiencies of railway operation and management and points out the significance of analyzing the efficiency of railways at the line level. Section 3 provides an overview of the urban railways in the TMA and highlights the unique features of the urban railway lines operating in the TMA. Section 4 describes the data scope and method that were used for the empirical analysis. Section 5 applies DEA to analyze three types of efficiencies and conducted Tobit regression to analyze how in-vehicle congestion rates are associated with these efficiencies, and the possible measures to improve them. At last, Section 6 concludes the main findings and implications of this study.

2. Literature review

The DEA, first developed by Charnes et al. (1978), is one of the most well-known approaches for efficiency analyses in various economic sectors, including railway transportation (Catalano et al., 2019). It has been applied to measuring railway efficiency at different levels, such as the country level and company level, examining the strategies of railway companies, comparing the efficiencies of railway operators, and evaluating policy measures, such as deregulation, privatization, and public subsidy (Holvad, 2020). Table 1 summarizes the major studies that have applied DEA in railway efficiency analyses. For example, Oum and Yu (1994) used DEA to measure the productive efficiency of railway systems in 19 OECD countries and applied a Tobit regression model to analyze the effects of public subsidies and managerial autonomy on efficiency. Chapin and Schmidt (1999) employed the DEA to estimate the efficiency of U.S. rail freight companies since deregulation and evaluated whether mergers have improved their efficiency. Cowie (1999)



Notes: 1. Financial performance is defined as the ratio of operating revenue to operating expenses.
2. Operating revenue is defined by line; operating expenses are estimated from the operating expenses by operator based on the ratio of passenger kilometers by line to the total passenger kilometers. (Umehara, 2016).

Data source: MLIT (2017), Institute for Transport Policy Studies (2018)

Fig. 1. Financial performance against the in-vehicle congestion rate of 18 urban railway lines. Notes: 1. Financial performance is defined as the ratio of operating revenue to operating expenses. 2. Operating revenue is defined by line; operating expenses are estimated from the operating expenses by operator based on the ratio of passenger kilometers by line to the total passenger kilometers. (Lan and Lin, 2003). Data source: Ministry of Land (2017a), Institute for Transport Policy Studies (2018).

Table 1
Major studies that applied DEA for railway efficiency analyses.

Authors	Research scopes	Objectives	Methodology
Oum and Yu (1994)	railway systems in 19 OECD countries	to analyze effects of public subsidies and managerial autonomy on efficiency	DEA
Chapin and Schmidt (1999)	US rail freight companies	to evaluate whether mergers have improved efficiency	DEA
Cowie (1999)	Swiss Private Railways	to estimate the technical efficiency, managerial efficiency, and organizational efficiency of private and public rail companies	DEA
Yu (2008)	40 global railways	to explore efficiency and effectiveness of railway companies that include both the un-storable feature of transportation service and the technological differences	TDEA, NDEA
Yu and Lin (2008)	20 selected railway firms in the world for the year 2002	to propose a multi-activity network data envelopment analysis model that incorporates production and consumption technologies	Multi-activity network DEA model
Jitsuzumi and Nakamura (2010)	53 railway operators in Japan	to analyze the causes of inefficiency in railway operations and calculate optimal subsidy levels.	DEA
Sekiguchi et al. (2010)	Urban railway operators in Japan	to analyze the efficiency of urban railways of different ownership including the third-sector railways	NDEA
Cantos et al. (2012)	23 European national rail systems from 2001 to 2008	to estimate the impacts of the deregulation on efficiency levels using alternative approaches and compare the results to analyze the potential differences between these approaches.	DEA (CRS, VRS), SFA
Oum et al. (2013)	three major railways and two major airlines in Japan during 1999–2007	to measures and compares social efficiency of railway firms and airlines in Japan incorporating he life cycle CO2emissions as a non-desirable output.	nonparametric directional output distance function
Doomernik (2015)	Four Asian and four European high-speed rail systems from 2007 to 2012	to investigate the production efficiency and service effectiveness of the high-speed systems, and identify the contributing factors in achieving high performance in production and marketing	NDEA, Malmquist Productivity Index
BaiZeng and Chui (2019)	China's railway sector over the period 2011–2015	to pre-evaluate the efficiency gains of M&A schemes using a combined approach of resampling DEA and the potential merger gains model	resampling DEA and the potential merger gains model

Notes: TDEA = traditional DEA; NDEA = network DEA; CRS = constant returns to scale; VRS = variable returns to scale; and SFA = Stochastic Frontier Analysis.

applied the DEA approach to estimate the technical efficiency, managerial efficiency, and organizational efficiency of private and public rail companies. Yu (2008) compared the results obtained from Traditional DEA and Network DEA, which measure the efficiency and effectiveness of railway companies, including both the un-storable feature of transportation services and technological differences. Jitsuzumi and Nakamura (2010) applied DEA to 53 railway operators in Japan to analyze the causes of inefficiency in railway operations and estimated the optimal subsidy levels.

In terms of the geographical scope, Oum et al. (1999) and Catalano et al. (2019) pointed out that the existing studies cover railway operators mainly in the U.S. and European countries. Catalano et al. (2019) reviewed 100 efficiency studies and categorized them by country. They showed that the comparison of railway systems in European countries received the most attention, including 38 studies out of 100, followed by railway operators in the U.S., which were analyzed in 15 studies. The remaining 12 studies include seven studies that analyzed the railway efficiency in the U.K. and six studies focusing on Japan (Holvad, 2020). Recently, more studies focusing on China's railway efficiency have been conducted. For example, BaiZeng and Chui (2019) combined resampling DEA and the potential merger gains model to pre-evaluate the efficiency gains of merger and acquisition schemes for China's passenger railways from 2011 to 2015.

Catalano et al. (2019) also analyzed the distribution of existing studies by the unit of analysis. They summarized that, out of 100 reviewed studies, 70 studies analyzed the efficiency of railway operators at the company level; 24 studies focused on large-scale comparisons at the national, regional, or county levels; five studies looked at the efficiency of city-wide systems or transit agencies, and a single study focused on the local units of firms. To the best of the authors' knowledge, no existing research has analyzed the railway efficiency at the line level. In this study, we made the first attempt to measure the efficiency of railway lines.

Despite the fact that the urban railways in the TMA have a high density of railway networks and significant ridership, empirical studies regarding the efficiency of Japanese railways are quite limited. The existing studies focusing on Japanese railway operators cover topics such as the efficiency of privatizing the former Japan National Railways (Sueyoshi et al., 1997), differences in the efficiencies of the private and public ownerships of railway operators (Ministry of Land, 2017b), optimal subsidy level (Jitsuzumi and Nakamura, 2010), efficiency of the third-sector urban railway operators (Sekiguchi et al., 2010), and social efficiency of railway firms compared with airlines (Oum et al., 2013).

As for the input and output variables used in DEA, in-vehicle congestion has been rarely considered. Holvad (2020) conducted a comprehensive review of the efficiency analyses in the railway sector and pointed out that quality attributes, such as speed, service punctuality, and service frequency, have been discussed in some studies. However, in-vehicle congestion has not yet been mentioned in any of the existing studies. As described earlier, Japanese railway operators have faced "social pressure" to reduce the in-vehicle congestion rate. Besides, the high density of railway networks, especially in the metropolitan center districts of the TMA, enables users to have multiple route choice options, indicating that urban railways in Japan are not entirely regionally monopolized. The operation of urban railway lines competes with that of other lines and other transportation modes in attracting travelers to the TMA. As a matter of fact, the past studies including the latest urban rail demand forecast model in the TMA, which was developed by the MLIT, incorporated in-vehicle congestion in its route choice model (Kato et al., 2010, 2017). This suggests that the in-vehicle congestion rate should be highlighted for evaluating business performance in the context of the urban railway industry, notably in the TMA.

3. Overview of the urban railways in the Tokyo Metropolitan Area

Tokyo is well known as a transit-oriented megacity (Cervero, 1998). According to the 2018 Person Trip Survey in Tokyo, the modal share of railways is highest (33%), followed by cars (27%) and walking (23%). The urban railway in the metropolitan area includes long-distance railways, suburban commuter railways, and subways (metros). The TMA covers a circular area with a radius of about 45 km, where the center is the Tokyo central station, and it includes the Tokyo, Chiba, Kanagawa, and Saitama prefectures. In addition, it has a population of over 30 million, which makes it one of the largest populated conurbations in the world. Tokyo's urban railway has unique history and characteristics, starting from the first railway service between Shinbashi and Yokohama in 1872 and the long historical development of urban railway networks covering the metropolitan area (Aoki et al., 2000). As of 2015, there are 32 railway companies in the metropolitan areas, including East Japan Railway Co. (JR East), other private/semi-private/public-owned railway companies, and metro companies. JR East used to be a national railway company, but it has been privatized since 1987. Semi-private railway companies are called third-sector companies, and they jointly belong to the private and public sectors. There are three metro companies in the following metropolitan areas: Tokyo Metro Co., Toei Transportation (operated by the Tokyo Metropolitan Government), and Yokohama Municipal Subway. According to Ministry of Land (2018), the total operational distance is 2459.1 km, including 887.2 km in JR East, 357.5 km in metros, and 1214.4 km in the other railway companies, while the total number of stations is 1,510, including 360 in JR East, 325 in metros, and 825 in the other railway companies. Japan has a long history in the railway industry, so each railway company owns, operates, and manages all the infrastructure assets, such as land, rail, electric facilities, and signal equipment, and provides railway services through operation (Ieda et al., 2001).

As shown by Ieda et al. (2001), the organizations operating railway lines in Tokyo form "territories." As the elasticity of the modal share with respect to the quality of service is low in each territory, the railway market in each territory is quite monopolized by each railway company. Thus, railway passengers have poor alternatives to choose between lines in their territories. Ieda et al. (2001) pointed out that this monopolistic situation discourages railway companies from improving service quality through investment, leading to underinvestment in Tokyo under the principle of profit maximization. Many major private railway companies in Tokyo have developed their railway networks without any subsidies from the government (Kurosaki, 2020). This was supported both by large-scale ridership from the high-population density areas in Tokyo and by the territory-based monopolistic conditions in the local railway market. Several private railway companies have developed residential areas along their railway lines when the population rapidly increased, which contributed to their sustainable gain of fare revenues and ridership. As shown in Chorus and Bertolini (2016), both local governments and private railway companies are involved in the development of railway corridors in Tokyo. However, recently, this has changed into commercial development in or near railway stations by railway companies (Zacharias et al., 2011). This can be called the Ensen-kaihatsu or Japanese-style railway area development (Taniguchi, 2018).

There is no integrated fare system in Tokyo (Kaneko, 2004). Many railway companies have their own networks in the territories where they operate, and they are managed quite independently. Direct-through operation services have been introduced to metros and other railway companies in Tokyo, where one rail line operated by a metro company is directly connected with another rail line operated by another company. This has led to better connectivity between different railway networks for the commuters traveling between suburban residential areas and the business district in the central area (Kato, 2014). However, each railway operator has its own fare table, so the railway passengers traveling across different railway lines are always required to pay an initial fare when entering another rail line. Note that the integrated smart card system is available in Tokyo, through which passengers can pass through the station gates of any railway company in the area, so passengers can avoid multiple cash payments (Kato et al., 2019).

For years, Tokyo has been suffering from in-vehicle congestion during morning peak hours. The chronic in-vehicle congestion leads to an increase in the dwell time at stations for getting on and off trains, which further leads to lower (scheduled) rail travel speeds (Abe and Kato, 2017). This issue has been identified in the urban railway development planning in Tokyo for many years, such as by Morichi et al. (2001) and Kato et al. (2017). The latest Tokyo's urban railway development master plan, which was made in 2016 (Council for Transport Policy, 2016), also highlighted the reduction of in-vehicle congestion in Tokyo's urban railways. Note that Tokyo's urban railway master plans have been developed every about 15 years since 1956, which has affected the investments of railway networks in the metropolitan area. As shown earlier, the poor motivation of private railway companies to invest in railways so as to increase railway capacity has led to insufficient improvements in the in-vehicle railway congestion for many years, notably after 2000.

Okamura (1999) pointed out that there is "social pressure" on Japanese railway operators to lower the in-vehicle congestion rate. This is a unique feature of Japanese railway operators, as they act in a way that enhances their corporate image and social reputation by upgrading their services. As many major railway companies operating in the TMA are publicly listed as private equity firms, they are highly concerned about equity holders. Recently, equity holders have strongly required railway companies to take corporate social responsibility. This has increased the sensitivity of railway companies to their social reputation, which is related to the concept of social pressure. Okamura (1999) showed that the social pressure on a specific company is not limited to their users but is extended from others, including the nonusers residing along the company's lines, residents in the metropolitan area, and other businesses and tourists who may be concerned with this area. Note that this pressure has been often highlighted by mass media (Okamura, 1999).

4. Data and methods

4.1. Scope and data

This study covers 18 major urban railway lines in the TMA of Japan, as illustrated in Fig. 2. Seven private or semi-private railway companies operate the 18 urban railway lines: Tokyo Metro, Tobu Railway, Seibu Railway, Tokyu Corporation, Odakyu Electric Railway, Keio Corporation, and Keisei Electric Railway. Except for Tokyo Metro, which mainly operates in the Tokyo central urban area, the other lines are commuter lines that connect the suburban areas and satellite cities with the urban center. The 18 lines were chosen based on a list of the congested urban railways in TMA, covering the major urban railways with in-vehicle congestion rates over 120% (Institute for Transport Policy Studies, 2018). The following data of the 18 railway lines in 2017 were collected for our empirical analysis: (1) in-vehicle congestion rates at the most congested section during the most congested period in a day (Institute for Transport Policy Studies, 2018), (2) line lengths (Ministry of Land, 2017a), (3) number of stations per line (Ministry of Land, 2017b), (4) vehicle kilometers and number of passengers per line (Ministry of Land, 2018), (5) operating revenue per line (Ministry of Land, 2018), (6) operating expenses per operator (Ministry of Land, 2018), and (7) passenger kilometers per line (Ministry of Land, 2018).

The operating revenue includes the ticket revenues and the

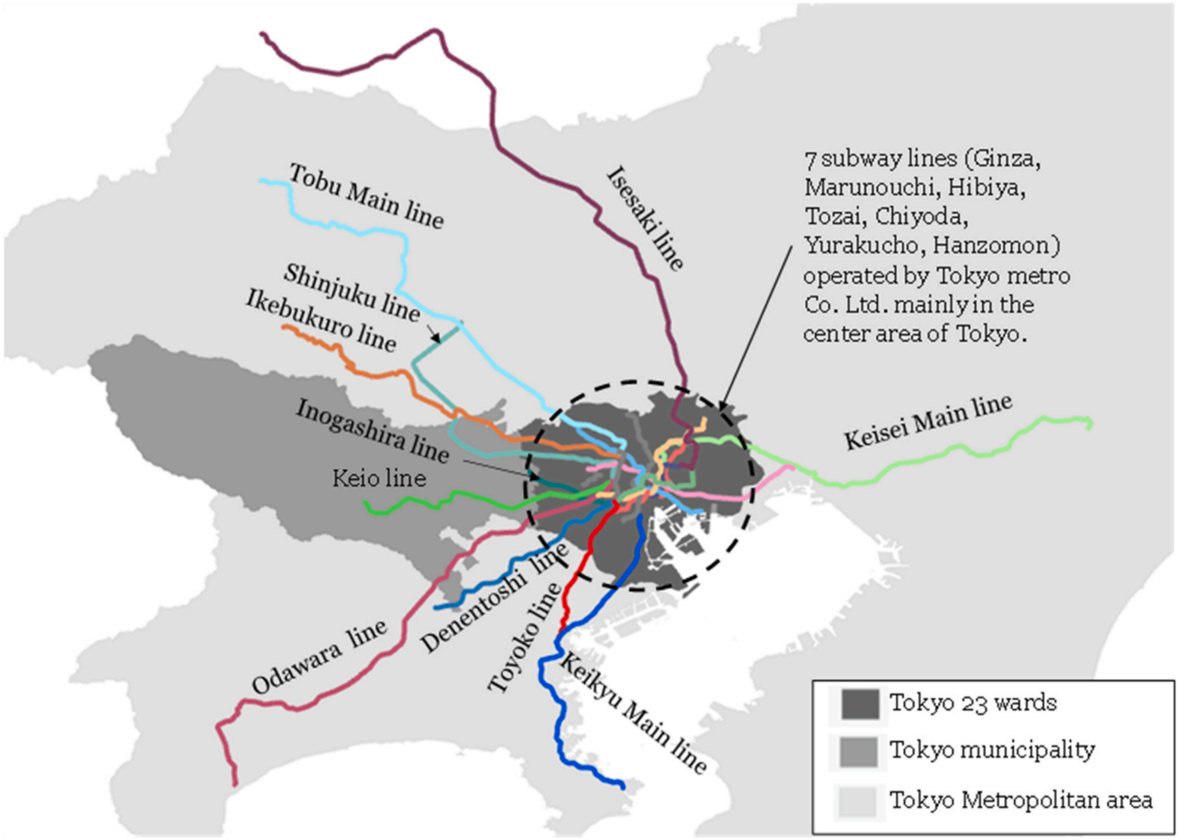


Fig. 2. Eighteen urban railway lines in the Tokyo Metropolitan Area.

miscellaneous income of transportation from side businesses, such as in-station/in-vehicle advertisements, passenger car rentals, and in-station/in-vehicle commercial businesses. The operating expenses cover the labor costs, which comprise salaries, allowances, welfare costs, and operating costs, which comprise maintenance, power, and utility costs. As the data of the operating expenses per line was not available, it was estimated based on the operating expenses per operator using the ratio of the passenger kilometers per line to the total passenger kilometers according to a method proposed in a previous study (Lan and Lin, 2003). The descriptive statistics of the dataset are shown in Table 2.

Table 2
Descriptive statistics of the dataset.

Data	Unit	Minimum	Maximum	Mean	Standard Deviation
In-vehicle congestion rate	(%)	127	199	161	17
Length of line (km)	(km)	13	115	43	27
Number of stations	(stations)	14	55	30	12
vehicle kms	(1 mil. km)	14	165	66	37
Annual passengers	(1 mil. per./year)	208	743	427	114
Fare revenue	(1 mil. JPY)	16,891	114,276	52,920	21,160
Miscellaneous transportation revenue	(1 mil. JPY)	290	10,262	4011	2056
Labor costs	(1 mil. JPY)	3213	32,680	13,474	6178
Operation costs	(1 mil. JPY)	4168	31,433	18,223	6733

Note: 1 JPY is equivalent to approximately 0.0089 US$ as of 2017.

4.2. Method

This study adopted the traditional DEA model, the Charnes, Cooper, and Rhodes model (CCR), which is based on the assumption of constant returns to scale for efficiency analysis. DEA is a widely used approach for measuring the relative efficiency of multiple decision-making units (DMUs) according to a ratio scale. The efficiency of a DMU is calculated by comparing its performance with the best performing units of the group (efficiency frontier). It maximizes the ratio of the weighted outputs to the weighted inputs based on the condition that the weights of other DMUs are all positive, and it is formulated as follows:

$$\text{Max.}\theta = \frac{u_1 y_{1k} + u_2 y_{2k} + \cdots + u_s y_{sk}}{v_1 x_{1k} + v_2 x_{2k} + \cdots + v_m x_{mk}}$$

$$\text{subject to} \quad \frac{u_1 y_{1j} + u_2 y_{2j} + \cdots + u_s y_{sj}}{v_1 x_{1j} + v_2 x_{2j} + \cdots + v_m x_{mj}} \leq 1 \ (j = 1, \cdots, n)$$

$$v_1, v_2, \cdots v_m \geq 0, \ u_1, u_2, \cdots u_s \geq 0$$

where θ is the efficiency score of the railway line k, x_r $(r = 1, \cdots, m)$ is a vector of the input variables, y_i $(i = 1, \cdots, s)$ is a vector of the output variables, and v_r $(r = 1, \cdots, m)$ and u_i $(i = 1, \cdots, s)$ denote the input weight and output weight, respectively. With the optimal solution (v^*, u^*), if $\theta^* = 1$ is efficient, $\theta^* < 1$ is inefficient. By aiming for a greater output with a smaller input, better efficiency can be achieved.

Three types of efficiency performance indicators, namely operational efficiency, cost efficiency, and revenue efficiency were measured in this study. Operational efficiency is the performance indicator to evaluate the operating efficiency with the consideration of quality-of-service.

Cost efficiency and revenue efficiency are the performance indicators to measure the financial robustness of the lines. The definitions and respective input and output variables in the three types of efficiency performance measures are summarized in Table 3.

First, operational efficiency is defined as the service output of the demand process against the infrastructure input, where the input variables are the line length and number of stations, while the output variables are the vehicle kilometers, number of passengers, and in-vehicle congestion rate. It denotes that greater service output with lower infrastructure input leads to higher operational efficiency. Moreover, the in-vehicle congestion rate, which represents service quality, is used as one of the output variables, and the 1/in-vehicle congestion rate is used to in the DEA calculations. Note that besides the in-vehicle congestion rate, other indicators such as operating speed and service punctuality are also important indicators to evaluate the quality of service. However, in the context of the TMA, these indicators are negligible as they are affected by the in-vehicle congestion. For instance, the average travel speed of urban rails may vary from 30 to 90 km/h depending on the type of services, such as local trains, commuter trains, or rapid commuter trains. Nevertheless, there is no significant difference in the average travel speed between lines within the TMA. Notably, most metro lines operate at speeds of 35–40 km/h (Japan Subway Association, 2019). Although the average travel speed during the morning peak may be slower than other times, this is due to the increased dwell time at railway stations under heavy in-vehicle congestion during peak hours. As for service punctuality, except for extreme weather conditions or human casualties, urban railways in the TMA normally operate on time. Further delays have been reported during peak hours due to longer dwell times when getting on and off the train at stations, mainly caused by severe in-vehicle congestion. Compared to other indicators, these facts can be seen as potential reasons why the in-vehicle congestion has become a major concern of society and the Government of Japan. Therefore, in this study, the in-vehicle congestion rate was incorporated into the output variables of operational efficiency. With a similar amount of infrastructure inputs, the lines with a greater amount of vehicle kilometers and a lower in-vehicle congestion rate are evaluated to be lines with high operational efficiency.

Next, the financial performance of the lines is measured by cost efficiency and revenue efficiency. The cost efficiency is defined as the service input against operating expense, where the input variables are the monetary value of operating expenses, including the labor costs and operating costs, while the output variables are the vehicle kilometers and the number of passengers. It denotes that the lines spending less expense have greater cost efficiency to provide the given amount of transportation services. The revenue efficiency is defined as the operating revenue against the service output, indicating the transportation service's monetary gains. The input variables are the vehicle kilometers and the number of passengers, while the output variables are the fare revenue and miscellaneous transportation revenue. The miscellaneous transportation revenue is considered as an output variable in addition to the fare revenue because side businesses, such as in-station retails and in-vehicle advertising, form an essential source of revenue for railway operators in TMA. It denotes that the lines gaining higher revenues have better cost efficiency to provide the given amount of transportation services.

Table 3
Definitions of the three types of efficiencies and their respective input and output variables.

Type of efficiency	Operational efficiency	Cost efficiency	Revenue efficiency
Definitions	Service output of demand process against the infrastructure input	Service output against operating expense	Operating revenue against service input
Input variables	Length of line, the number of stations	Labor costs, operating costs	Vehicle kilometers, No. of passengers
Output variables	Vehicle kilometers, No. of passengers, 1/in-vehicle congestion rate	Vehicle kilometers, No. of passengers	Fare revenue, miscellaneous transportation revenue

5. Results

5.1. Efficiency analysis

First, Table 4 shows the operational efficiency results and the improvement rates of the 18 lines. An improvement rate represents the degree of improvement in the current value against the target value. A positive improvement rate indicates a shortage that needs to be increased, while a negative improvement rate indicates a surplus that needs to be reduced. There are two orientation measures for the target value: input-orientation and output orientation measures. The input orientation measure estimates the maximum possible proportional reduction in input variables under a fixed output at the current status, while the output orientation measure estimates the maximum possible proportional increase in output values under a fixed input at the current status. The improvement rates are defined as:

$$IRI_{rk} = \frac{100 \cdot (\overline{x}_r - x_{rk})}{x_{rk}}$$

$$IRO_{ik} = \frac{100 \cdot (\overline{y}_i - y_{ik})}{y_{ik}}$$

where IRI_{rk} and IRO_{ik} are the rth input- and ith output-oriented improvement rates of line k, respectively, and $\overline{x}_r$ and $\overline{y}_i$ are the target values of the rth input and ith output of line k, respectively.

Note that the output-orientation measure was applied to the computation of the operational efficiency because we assumed that the current value of the infrastructure input cannot be easily changed. The results showed that the Keio, Inokashira, and Odawara lines are the most efficient suburb lines and that the Ginza and Hanzomon lines are the most efficient metro lines. Regarding the rest of the lines that failed to achieve efficient operation, the improvement rates reveal the extent to which output variables can be improved if a fully efficient operation strategy can be realized. For example, let us take a close look at the Keio and Denentoshi lines. Fig. 1 shows that these lines have similar financial performance but different congestion rates. As shown in Table 4, the operational efficiency of the Keio line is 1.00 and that of the Denentoshi line is 0.84. If the vehicle kilometer and number of passengers of the Denentoshi line would be increased by 20% and the congestion rate would be reduced from 185% to 133%, the efficiency score of the Denentoshi line could reach that of the Keio line. Although the two lines have similarities in their operating kilometers, number of stations, and number of passengers, they have significantly different vehicle kilometers. Thus, most probably, this has resulted in a higher congestion rate in the Denentoshi line than that in the Keio line, suggesting that the vehicle capacity needs to be increased for the Denentoshi line to reduce the in-vehicle congestion.

Second, Table 5 shows the results of the cost efficiency, target value, and improvement rates of the 18 lines. Note that the input-orientation approach was applied to the computation of cost efficiency. The results give an insight on how much operating expense can be reduced compared to the fully efficient lines for providing the same amount of transportation service. It can be seen that the Isesaki, Shinjuku, Ikebukuro, Inokashira, and Ginza lines are the highest performers in this indicator and that the Toyoko, Tozai, Chiyoda are the poorest performers. The improvement rates reveal that the inefficient lines need to reduce their labor and operating costs for providing the same amount of transportation service as the most efficient lines. Finally, let us look at the average efficiency of suburb railways and metro systems. We can see

Table 4
Operational efficiency scores and improvement rates of the 18 urban railway lines in the TMA.

Operators	Lines	Operat. Effici.	Input variables						Output variables								
			Length of line (km)			No. of stat.			Vehicle kms (1 million km)			No. of pax. (1 million per./y)			1/cong. rate		
			Curr. value	Targ. value	Improv. rate	Curr. value	Targ. value	Improv. rate	Curr. value	Targ. value	Improv. rate	Curr. value	Targ. value	Improv. rate	Curr. value	Targ. value	Improv. rate
Tobu	Isesaki	0.564	114.5	88.1	−23%	55	55	0%	97.9	173.4	77%	387.1	1047.4	171%	0.67	1.19	77%
	Mainline	0.830	75	59.7	−20%	38	38	0%	97.2	117.1	20%	374.2	748.4	100%	0.73	0.88	20%
Seibu	Shinjyuku	0.886	47.5	44.9	−6%	29	29	0%	77.8	87.8	13%	326.8	585.7	79%	0.63	0.71	13%
	Ikebukuro	0.880	57.8	49.1	−15%	31	31	0%	84.9	96.5	14%	388.2	601.8	55%	0.61	0.7	14%
Keisei	Mainline	0.627	67.2	60.2	−10%	42	42	0%	72.9	116.2	59%	233.4	948.5	306%	0.79	1.26	59%
Keio	Keio	1.000	37.9	37.9	0%	34	34	0%	111.6	111.6	0%	527.4	527.4	0%	0.60	0.6	0%
	Inokashira	1.000	12.7	12.7	0%	17	17	0%	13.8	13.8	0%	207.8	207.8	0%	0.68	0.68	0%
Odakyu	Odawara	1.000	82.5	82.5	0%	47	47	0%	164.8	164.8	0%	743.2	743.2	0%	0.66	0.66	0%
Tokyu	Toyoko	0.926	24.2	24.2	0%	21	21	0%	49.6	53.6	8%	449.5	485.3	8%	0.60	0.69	16%
	Denentoshi	0.835	31.5	31.5	0%	27	27	0%	64.0	76.6	20%	465.2	556.9	20%	0.54	0.75	38%
Keikyu	Mainline	0.610	56.7	56.7	0%	50	50	0%	93.0	152.6	64%	444.1	906.3	104%	0.69	1.14	64%
Metro	Ginza	1.000	14.3	14.3	0%	19	19	0%	21.8	21.8	0%	415.6	415.6	0%	0.63	0.63	0%
	Marunouchi	0.713	27.4	27.4	0%	28	28	0%	31.9	47.5	49%	493.3	691.6	40%	0.61	1.04	72%
	Hibiya	0.855	20.3	20.3	0%	21	21	0%	29.7	35.0	18%	440.5	515.6	17%	0.64	0.78	22%
	Tozai	0.964	30.8	30.8	0%	23	23	0%	57.9	60.1	4%	529.4	549.0	4%	0.50	0.76	51%
	Chiyoda	0.843	24	24	0%	20	20	0%	36.9	44.6	21%	463.1	549.4	19%	0.56	0.83	47%
	Yurakucho	0.752	28.3	28.3	0%	24	24	0%	46.1	61.3	33%	412.5	571.3	38%	0.61	0.82	33%
	Hanzomon	1.000	16.8	16.8	0%	14	14	0%	31.2	31.2	0%	384.6	384.6	0%	0.58	0.58	0%

that the average cost efficiency of metro lines is higher than that of suburb lines. Due to the difficulty of maintenance and operation, metro lines spend more operating and labor costs than suburb railways. In particular, the Tozai metro line, which has the highest in-vehicle congestion rate, demonstrates the lowest cost efficiency. In the next section, we will determine how the in-vehicle congestion rate is associated with cost efficiency using Tobit regression.

Third, Table 6 shows the efficiency scores and improvement rates of the revenue efficiency. Note that the output-orientation measure was applied to the computation of the revenue efficiency. This indicator reveals that given the same amount of transportation service, how much revenue can be improved compared to the most efficient line. The results showed that the Isesaki and Ginza lines are the most efficient ones, and Tobu main, Shinjyuku, Ikebukuro, and Keio lines are the poorest performers, which are all suburb lines. The results also suggested that average revenue efficiency in metro lines is significantly higher than that of suburb lines. It is reasonable that metro lines gain a higher fare revenue because our analysis results of cost efficiency revealed a higher unit cost of metro line. In particular, the average improvement rate of miscellaneous transportation revenue of suburb lines is considerably higher than that of metro lines. This is because the metro lines are located at urban centers where all the stations are flourished by numerous in-station shops that contribute to miscellaneous revenue. Meanwhile, most stations along the suburb lines could not gain much in-station sales except for the satellite city stations and terminal stations in urban center. It should be noted, however, Isesaki line is an exceptional case. Its miscellaneous revenue is approximately 10.3 billion JPY, ranking at the top of all lines although it is categorized into suburb line. This is probably because Isesaki line is connected with the Tokyo Sky Tree, which is a well-known landmark tourism spot in Tokyo that attracts many tourists from both Japan and abroad. Note that the Tokyo Sky Tree is a broadcasting and observation tower at Sumida City in Tokyo, and it was developed jointly with commercial facilities by the Tobu Railway Co. and its group companies in 2012.

As shown in Fig. 1, the Isesaki, Inokashira, and Odawara lines have similar congestion rates but different financial performances. Their efficiency scores are 1.00, 0.83, and 0.73, respectively. Suppose the Inokashira line achieves the same revenue efficiency as the Isesaki line and provides the same transportation services. In that case, it will increase its fare revenue by 20% and miscellaneous revenue by 725%. Similarly, for the Odawara line, the increases would be 37% and 358%, respectively. This suggests that increasing the miscellaneous transportation revenue would be a good strategy to maintain the revenue. The Inokashira line appears to have the largest improvement rate in the miscellaneous transportation revenue. This may be first because its operating distance is much shorter than that of the others and second because it does not have large-scale tourist attractions along the railway line, which makes it difficult to generate income from side businesses, such as in-station commercial businesses.

5.2. Tobit regression analysis

Tobit regression was employed to examine the relationship between in-vehicle congestion rates and DEA efficiency scores to understand how the in-vehicle congestion rate is associated with these three efficiencies. The Tobit model is extensively used in combination with DEA to identify factors that affect efficiency scores, as it is particularly appropriate for performing regression analysis on censored data because the efficiency scores are limited to the range of 0–1 (Hoff, 2007).

First, prior to estimating the Tobit model for operational efficiency, we compared the operational efficiencies scores with and without in-vehicle congestion rate as an output variable for clarifying how the in-vehicle congestion rate is associated with operational efficiency. Table 7 summarizes the operational efficiency scores of the three categories of lines in which the 18 lines were grouped into three categories according to the in-vehicle congestion rate. This indicates that the

Table 5
Cost efficiency scores and improvement rates of the 18 urban railway lines in the TMA.

Operator	Lines	Cost effici.	Input variables						Output variables					
			Labor costs (1 mil. JPY)			Operating costs (1 mil. JPY)			vehicle kms (1 mil. km)			No. of pax.(1 mil. per./y)		
			Curr. value	Targ. value	Improv. rate	Curr. value	Targ. value	Improv. rate	Curr. value	Targ. value	Improv. rate	Curr. value	Targ. value	Improv. rate
Tobu	Isesaki	1.000	11,037	11,037	0%	22,293	22,293	0%	97.9	97.9	0%	387.08	387.08	0%
	Main line	0.922	11,884	10,962	−8%	24,005	22,143	−8%	97.2	97.2	0%	374.22	384.46	3%
Seibu	Shinjyuku	1.000	13,231	13,225	0%	13,443	13,438	0%	77.8	77.8	0%	326.78	355.79	9%
	Ikebukuro	1.000	14,429	14,429	0%	14,661	14,661	0%	84.9	84.9	0%	388.18	388.18	0%
Keisei	Main line	0.908	11,289	10,249	−9%	16,133	14,647	−9%	72.9	72.9	0%	233.38	310.17	33%
Keio	Keio	0.895	18,922	16,939	−10%	24,546	21,974	−10%	111.6	111.6	0%	527.44	527.44	0%
	Inokashira	1.000	3213	3213	0%	4168	4168	0%	13.8	13.8	0%	207.77	207.77	0%
Odakyu	Odawara	0.905	32,680	28,008	−14%	31,433	28,458	−9%	164.8	164.8	0%	743.24	753.47	1%
Tokyu	Toyoko	0.596	15,697	9351	−40%	19,784	11,785	−40%	49.6	49.6	0%	449.51	449.51	0%
	Denentoshi	0.647	17,232	11,154	−35%	21,719	14,059	−35%	64.0	64.0	0%	465.19	465.19	0%
Keikyu	Main line	0.816	15,389	12,565	−18%	24,785	20,237	−18%	93.0	93.0	0%	444.14	444.14	0%
Suburb lines average		0.881	15,000	12,830	−12%	19,725	17,078	−12%	84.315	84.315	0%	413.36	424.8	4%
Metro	Ginza	1.000	5919	5919	0%	8479	8479	0%	21.8	21.8	0%	415.58	415.58	0%
	Marunouchi	0.762	9829	7490	−24%	14,079	10,729	−24%	31.9	31.9	0%	493.29	493.29	0%
	Hibiya	0.715	9480	6778	−29%	13,579	9709	−29%	29.7	29.7	0%	440.55	440.55	0%
	Tozai	0.545	18,792	10,233	−46%	26,917	14,657	−46%	57.9	57.9	0%	529.42	529.42	0%
	Chiyoda	0.570	13,277	7564	−43%	19,018	10,834	−43%	36.9	36.9	0%	463.07	463.07	0%
	Yurakucho	0.660	12,234	8079	−34%	17,523	11,573	−34%	46.1	46.1	0%	412.48	412.48	0%
	Hanzomon	0.791	7993	6326	−21%	11,449	9061	−21%	31.2	31.2	0%	384.58	384.58	0%
Metro lines average		0.720	11,075	7484	−28%	15,864	10,720	−28%	36.5	36.5	0%	448.42	448.4	0%

Table 6
Revenue efficiency scores and improvement rates of the 18 urban railway lines in the TMA.

Operators	Lines	Rev. Effici.	Input variables						Output variables					
			vehicle kms (1 mil. km)			No. of pax.(1 mil. per./y)			Fare rev. (1 mil. JPY)			miscell. trans. rev. (1 mil. JPY)		
			Curr. value	Targ. value	Improv. rate	Curr. value	Targ. value	Improv. rate	Curr. value	Targ. value	Improv. rate	Curr. value	Targ. value	Improv. rate
Tobu	Isesaki	1.000	97.9	97.9	0%	387.1	387.1	0%	90,372	90,372	0%	10,262	10,262	0%
	Main line	0.663	97.2	94.6	−3%	374.2	374.2	0%	57,936	87,368	51%	4722	9921	110%
Seibu	Shinjyuku	0.617	77.8	77.8	0%	326.8	326.8	0%	44,917	72,792	62%	983	8277	742%
	Ikebukuro	0.636	84.9	84.9	0%	388.2	388.2	0%	51,499	80,971	57%	3078	9226	200%
Keisei	Main line	0.725	72.9	59.0	−19%	233.4	233.4	0%	39,511	54,486	38%	2744	6187	125%
Keio	Keio	0.612	111.6	111.6	0%	527.4	527.4	0%	65,643	107,259	63%	3233	12,231	278%
	Inogashira	0.833	13.8	13.8	0%	207.8	207.8	0%	16,891	20,284	20%	290	2395	725%
Odakyu	Odawara	0.729	164.8	164.8	0%	743.2	743.2	0%	114,276	156,666	37%	3896	17,845	358%
Tokyu	Toyoko	0.860	49.6	49.6	0%	449.5	449.5	0%	50,052	58,233	16%	5413	6765	25%
	Denentoshi	0.766	64.0	64.0	0%	465.2	465.2	0%	53,250	69,508	31%	5194	8020	54%
Keikyu	Main line	0.733	93.0	93.0	0%	444.1	444.1	0%	65,736	89,656	36%	2444	10,227	318%
Suburb line average		0.743	84.3	82.8	−2%	413.4	413.4	0%	59,098	80,690	37%	3842	9214	267%
Metro	Ginza	1.000	21.8	21.8	0%	415.6	415.6	0%	36,278	36,278	0%	4318	4318	0%
	Marunouchi	0.988	31.9	31.9	0%	493.3	493.3	0%	46,910	47,480	1%	5319	5612	6%
	Hibiya	0.988	29.7	29.7	0%	440.5	440.5	0%	42,736	43,248	1%	3534	5105	44%
	Tozai	0.818	57.9	57.9	0%	529.4	529.4	0%	55,829	68,231	22%	5437	7928	46%
	Chiyoda	0.925	36.9	36.9	0%	463.1	463.1	0%	45,902	49,637	8%	4131	5827	41%
	Yurakucho	0.770	46.1	46.1	0%	412.5	412.5	0%	41,507	53,875	30%	3306	6256	89%
	Hanzomon	0.800	31.2	31.2	0%	384.6	384.6	0%	33,322	41,646	25%	3892	4886	26%
Metro line average		0.899	36.5	36.5	0%	448.4	448.4	0%	43,212	48,628	13%	4277	5705	36%

average operational efficiency score with the in-vehicle congestion rate in the lower congestion category is significantly higher than that without the in-vehicle congestion rate. In contrast, in the medium and high congestion categories, the average scores with in-vehicle congestion rates are slightly higher or the same as the scores without in-vehicle congestion.

Table 8 shows the estimation results of Tobit model, in which in-vehicle congestion rate is an independent variable and operational efficiency score without in-vehicle congestion rate is the dependent variable. This indicates that in-vehicle congestion rate is positively associated with efficiency scores. Without incorporating in-vehicle congestion into operational efficiency, a line with a high congestion rate tends to get a greater efficiency score. This may greatly underestimate the efficiency of the lines with relatively lower congestion, in which many efforts have been made to improve operational efficiency to reduce congestion. This suggests that the incorporation of in-vehicle congestion rate into operational efficiency enables to reflect the quality-of-service of the railway operation into the efficiency score.

Second, Table 9 shows the estimation results of the Tobit model for cost efficiency scores. The results indicate that the in-vehicle congestion rate has a significant negative association with cost efficiency scores. This suggests that lines with severe in-vehicle congestion spend more on labor and operating costs for a given transportation service than lines with less severe in-vehicle congestion. Note that the in-vehicle congestion rate is expressed as the level of congestion on the most congested section of a given line during the busiest time of the day. Given the same amount of service output represented by train kilometers and the number of passengers in the current study, the higher the in-vehicle congestion rate is, the more uneven the distribution of traffic demand may be across the sections in the line and/or across the time of day.

Table 7
Operational efficiency scores with/without in-vehicle congestion rate in output variables.

In-vehicle congestion rate	Operational efficiency scores		
		Without congestion rate	With congestion rate
Lower category (6 lines) 151% or lower	Mean	0.6542	0.7719
	Standard Deviation	0.1725	0.1815
Medium category (6 lines) 152%–165%	Mean	0.8109	0.8477
	Standard Deviation	0.0953	0.0940
Higher category (6 lines) 166% or higher	Mean	0.9281	0.9281
	Standard Deviation	0.0678	0.0678

Table 8
Estimation results of Tobit model for operational efficiency score without in-vehicle congestion rate.

	Coeff.	Std. Err.	z-value	P>|z|	[0.025	0.975]
Intercept	−0.2104	0.366	−0.575	0.565	−0.927	0.507
In-vehicle congestion	0.6384	0.227	2.818	0.005[a]	0.194	1.082
Log (Sigma)	−1.8362	0.202	−9.089	0.000	−2.232	−1.440
Log-likelihood ratio 6.2						
Log-likelihood p-value 0.013						

[a] Significant at 95-percent confidence level.

Table 9
Estimation results of Tobit model for cost efficiency scores.

	Coeff.	Std. Err.	z-value	P>|z|	[0.025	0.975]
Intercept	1.9076	0.341	5.589	0.000[a]	1.239	2.577
In-vehicle congestion	−0.6659	0.210	−3.164	0.002[a]	−1.078	−0.253
Log (Sigma)	−1.9135	0.200	−9.559	0.000	−2.306	−1.521
Log-likelihood ratio 7.7						
Log-likelihood p-value 0.005						

[a] Significant at 95-percent confidence level.

Railway operators are then required to deploy more labor and trains to meet the peak demand, resulting in lower cost efficiency.

Third, Table 10 shows the estimation results of the Tobit model for revenue efficiency scores. This indicates a positive association between the in-vehicle congestion and the revenue efficiency scores, but its statistical significance is weak. Then, we further split the two output variables of revenue efficiency to distinguish the association between in-vehicle congestion and fares from miscellaneous revenue. An output-oriented measure was applied to calculate the revenue efficiency. We calculated the output shortage slack of fare and miscellaneous revenue for inefficient lines. Table 11 shows the estimation results of the Tobit model using the fare and miscellaneous revenue as dependent variables.

Table 10
Estimation results of Tobit model for revenue efficiency scores.

	Coeff.	Std. Err.	z-value	P>|z|	[0.025	0.975]
Intercept	0.6522	0.325	2.005	0.045	0.015	1.290
In-vehicle congestion	0.0986	0.201	0.490	0.624	−0.296	0.493
Log (Sigma)	−1.9518	0.183	−10.692	0.000	−2.310	−1.594
Log-likelihood ratio 0.2						
Log-likelihood p-value 0.626						

The independent variables are in-vehicle congestion rate and transport density. The transport density is defined as the average number of passengers per day, calculated from the passenger kilometers per km per day.

Table 11 indicates that the estimated coefficients of in-vehicle congestion are significantly negative in both models, while transport density is significantly positive. They suggest that the lower the in-vehicle congestion rates, the more the oversized shortage slacks, and the lower the revenue efficiency. In other words, high in-vehicle congestion contributes to a better performance of revenue efficiency. In particular, the impact of in-vehicle congestion on miscellaneous revenue is greater than that of fare revenue. A possible explanation is that the congested lines in the TMA tend to receive more attention from society, attracting larger in-vehicle advertisements. In addition, the congested lines are generally connected with terminal stations where huge in-station retailing sales are expected. In terms of transport density, the higher the density, the lower the revenue efficiency. Given the same transportation service, the lines with higher transport density earn less revenue than those with lower density. In other words, the unit revenue of high-density lines is less than the unit revenue of low-density lines. In the Japanese railway industry, the yardstick regulation has been applied since 1997. This allows ticket fares to be determined based on standard costs, where the unit cost of high-density lines is lower than that of other lines, resulting in lower unit revenue for high-density lines (Mizutani and Usami, 2016).

5.3. Synthesis analysis

For a comprehensive comparison with respect to the three types of efficiencies across the 18 railway lines, we first classified these lines into five categories by applying Ward's hierarchical clustering method (see Fig. 3). Fig. 4 illustrates the five categories: Category 1 (low operational efficiency but high cost/revenue efficiency lines), Category 2 (low operational/cost efficiency lines), Category 3 (low cost efficiency lines), Category 4 (high operational/cost efficiency lines), and Category 5 (low revenue efficiency lines). Such categorization enabled us to discuss the unique strategies that are required for improving the efficiencies by category. First, the lines of Category 1 realized high revenue and cost efficiencies despite their operational inefficiency. This implies that these lines can achieve good financial performance even if their transportation service output and consumption are relatively poor. For example, the cost and revenue efficiencies of the Isesaki line have a score of 1.00, while its operational efficiency only has a score of 0.564. Although the Isesaki line is a suburb line with a long operating distance and limited transportation demand, it successfully achieved high cost and revenue efficiencies through the efforts of cost control and the development of side businesses, such as tourist attractions (Tokyo Sky Tree). Second, the lines of Category 2 are poor performers with regards to both operational and cost efficiencies. They require market promotion to attract more passengers at a low cost. Third, the lines of Category 3 are good performers in terms of the operational and revenue efficiencies, but they suffer from poor performance in terms of cost efficiency. Thus, cost reduction both on labor cost and operating cost is required for these lines. For instance, the installation of platform screen doors or further automating railway operation can be possible measures to improve their cost efficiency. Fourth, the lines of Category 4 realized high operational, cost, and revenue efficiencies in a balanced manner. The Ginza, Inogashi, Keio, and Odawara lines are located in populated areas, which make them have high demand, thus directly contributing to their revenue gains and resulting in good financial performance. Finally, the lines of Category 5 realized high operational and cost efficiencies at the expense of low revenue efficiency. These lines may need to increase the miscellaneous transportation revenue to improve their efficiency. For instance, the improvement of the connectivity at the major terminal stations may enable the Shinjuku and Ikebukuro lines to enjoy their advantages of the miscellaneous revenue through in-station retail

Table 11
Estimation results of Tobit models for output shortage slacks of fare and miscellaneous revenue.

Fare revenue model	Coeff.	Std. Err.	z-value	P>|z|	[0.025	0.975]
Intercept	6.5816	3.458	1.903	0.057	−0.195	13.359
In-vehicle congestion	−4.8035	2.599	−1.848	0.065[b]	−9.897	0.290
Transport density	0.8575	0.416	2.059	0.039[a]	0.041	1.674
Log (Sigma)	0.2894	0.180	1.605	0.109	−0.064	0.643
Log-likelihood ratio 4.2						
Log-likelihood p-value 0.122						
Miscellaneous revenue model	Coeff.	Std. Err.	z-value	P>|z|	[0.025	0.975]
Intercept	20.922	8.705	2.404	0.016	3.861	37.983
In-vehicle congestion	−15.493	6.544	−2.368	0.018[a]	−28.319	−2.667
Transport density	2.5225	1.050	2.403	0.016[a]	0.465	4.580
Log (Sigma)	1.2126	0.180	6.732	0.000	0.860	1.566
Log-likelihood ratio 5.9						
Log-likelihood p-value 0.054						

[a] Significant at 95-percent confidence level.
[b] Significant at 90-percent confidence level.

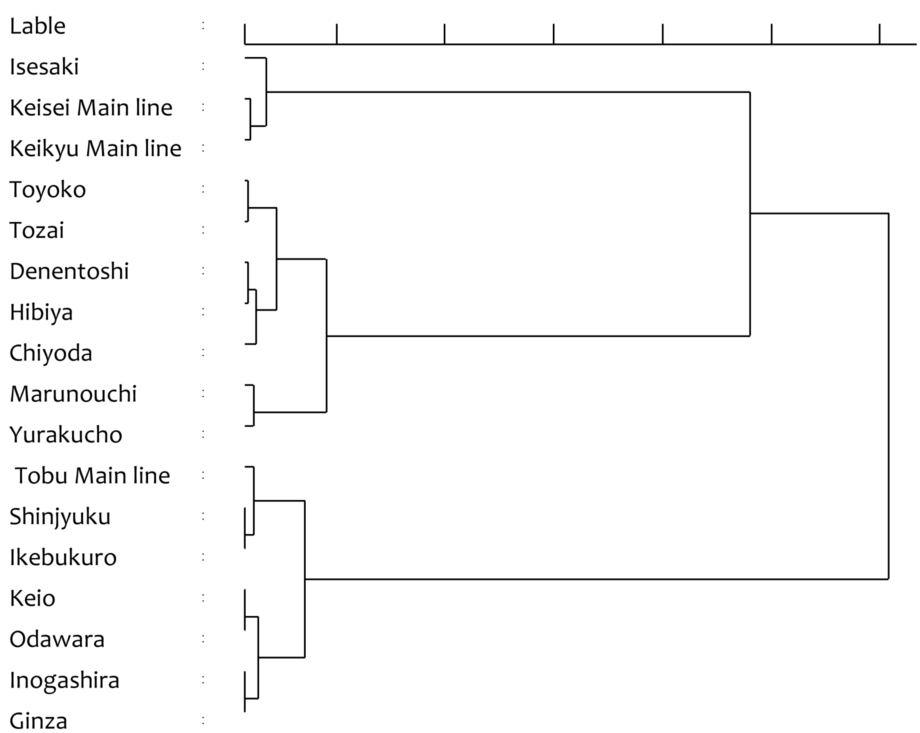


Fig. 3. Categorization of the lines using Ward's hierarchical clustering method.

businesses and in-vehicle advertisements.

6. Conclusions

This study quantitatively analyzed the line-level efficiencies of 18 urban railways in the TMA using the traditional DEA method incorporating financial performance and in-vehicle congestion. Three types of efficiencies, namely operational efficiency, cost efficiency, and revenue efficiency were evaluated and compared among them. The critical factors affecting the railway efficiencies were discussed, and possible strategies for improving the efficiencies were examined through descriptive comparisons of the selected lines and a categorized synthesis analysis covering all the lines. The results revealed the degree to which the vehicle kilometer and vehicle capacity should be increased to improve operational efficiency. They also showed that a decrease in labor and operating costs and an increase in the miscellaneous transportation revenue can contribute to the improved cost and revenue efficiencies, respectively. Tobit analysis showed that in-vehicle congestion rate has a negative association with cost efficiency, but a positive association with revenue efficiency, in particular miscellaneous revenue. This implies that lines with high in-vehicle congestion rate may not necessarily have a high financial performance.

Our findings should contribute to the development of business strategies for the local railway companies operating each line in the TMA, as in this study, a diagnosis of the current efficiency statuses in each line and the suggestion of potential measures for improving the efficiency of each line were made possible. Additionally, the proposed approach regarding the analyses of the railway efficiencies incorporating financial performance and in-vehicle congestion can also be useful for the integrated evaluation of urban railways in other railway-oriented cities. This is because many major cities must have faced urban railway service problems similar to those of the TMA, where railway operators suffer from the trade-off association between profitability and in-vehicle congestion.

Although this study successfully contributed to the integrated evaluation of the railway efficiencies incorporating financial performance

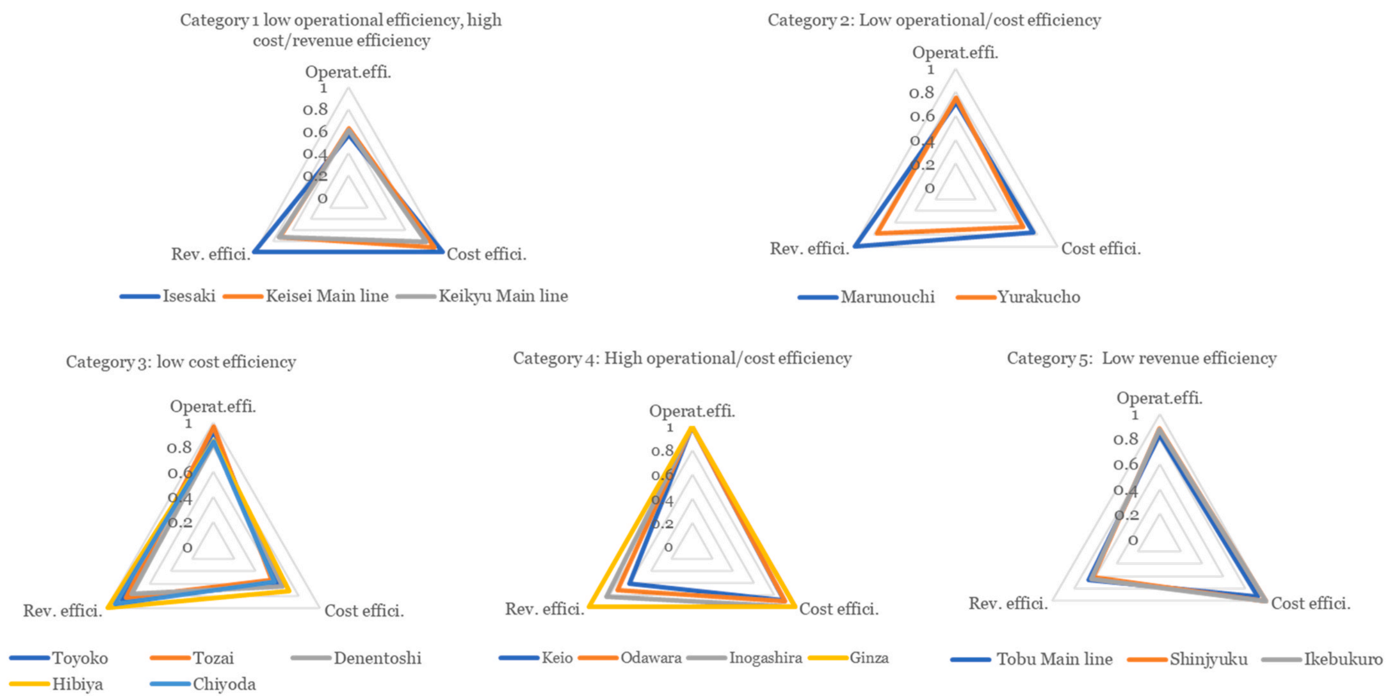


Fig. 4. Comparisons among the five categories of the 18 lines based on the efficiency analyses.

and in-vehicle congestion simultaneously, there are still many remaining issues. First, due to the unavailability of line-based data, this study examined the above-mentioned efficiencies using line-based data, which was estimated based on the passenger kilometer per line using the total passenger kilometer of the operators. However, this method may not represent the exact line-based data. Additionally, this approach may not be suitable when railway companies provide multiple types of railway services, such as inter-regional railway, high-speed railway, and rural railway services. This is one of the reasons that this study excluded JR East, which provides other railway services and urban railway services, from the scope of the empirical analysis. Second, this study defined the three types of the above-mentioned efficiencies, but their characteristics may not be well discussed, so they should be further elaborated. Notably, the associations among them should be examined more from theoretical viewpoints. Third, this study assumed that line-based in-vehicle congestion is represented by the congestion at the most congested section on a line during the most congested period in a day. This definition of in-vehicle congestion was used in this study because policymakers and passengers in the TMA are typically concerned with the most serious in-vehicle congestion on each line. However, railway companies should take account of dynamic changes in in-vehicle congestion throughout the day and take care of all the congested sections on railway lines. To examine the entire service levels relating to the in-vehicle congestion of urban railways, we should extend its coverage to a more general one. In addition, due to data limitations, this study only covers urban rail lines where the in-vehicle congestion rate is over 120%. Note that this study used the data on in-vehicle congestion rates from the database of the Institute for Transport Policy Studies in Japan,[1] a public research institute. Unfortunately, this database does not include in-vehicle congestion rates for lines with low congestion levels. Last but not least, international comparisons of the efficiencies of urban railways across major cities may be valuable for the benchmarking of different services from the perspective of three efficiency types, which were proposed in this study.

[1] Note this institute has been reorganized and renamed into Japan Transport and Tourism Research Institute since June 2016.

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Yiping Le: Conceptualization, Methodology, Writing – original draft, preparation. **Minami Oka:** Data curation, Investigation, Visualization. **Hironori Kato:** Conceptualization, Methodology, Supervision, Writing – review & editing, All authors have read and agreed to the published version of the manuscript.

Declaration of competing interest

The author declares no conflict of interest.

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