How Exogenous Factors and Approaches Affect the Performance Measurement of Urban Rail Services

Rizal Shahurein bin Kamaruddin

Submitted in accordance with the requirements for the degree of

Doctor of Philosophy

The University of Leeds

Institute for Transport Studies

May 2023

Intellectual Property Statement

Acknowledgement

I want to express my deepest gratitude and appreciation to all those who have supported and guided me throughout the completion of this thesis. Primarily, I am immensely grateful to my supervisors, Professor Andrew Smith and Professor Phill Wheat, for their unwavering guidance, valuable insights, and continuous encouragement. Their expertise, patience, and commitment to excellence have been instrumental in shaping the direction and quality of this research. I am truly fortunate to have had their mentorship and support. I am also deeply thankful to Dr Yeonjung Song, who volunteered her time and provided the necessary data for this study. Without her contributions, this research would not have been possible.

I want to extend my heartfelt appreciation to the Institute for Transport Studies (ITS) faculty members and staff, whose dedication and commitment to academic excellence have provided me with a stimulating and nurturing environment to conduct my research. I am grateful for the resources, facilities, and opportunities this institution has provided me throughout my academic journey.

My gratitude extends to my family and friends, whose unwavering support, understanding, and encouragement have been the pillars of strength throughout this endeavour. Their belief in my abilities and constant motivation has fuelled my determination to overcome challenges and pursue excellence.

Lastly, I acknowledge the countless researchers, scholars, and authors whose work laid the foundation for this thesis. Their contributions to Transport Economics have shaped my understanding and provided me with a wealth of knowledge to draw upon.

This thesis would not have been possible without the individuals above and the institutions' support, guidance, and encouragement. Their contributions have played a significant role in shaping my academic journey, and for that, I am deeply grateful. Thank you.

Rizal Shahurein bin Kamaruddin

Abstract

Running urban rail services can be costly; in some contexts, it requires subsidy. Therefore, ensuring that costs are kept in line is vital as it affects government expenditure and passenger fares. This condition motivates studies that understand the cost structure and whether firms operate efficiently. The empirical work presented in this thesis centres on urban rail in Japan as its primary focus. This thesis comprises three interrelated research studies. Research Study 1 aims to understand the cost structure of each urban rail mode in Japan. Research Study 2 explores the ownership effect on cost efficiency. Research Study 3 further explores ownership and other effects on cost efficiency, service effectiveness, and cost effectiveness. This thesis utilised the trans-log cost function and DEA-Tobit regression to achieve the research aims. The trans-log cost function is parametric, while DEA-Tobit regression is semi-parametric. Nevertheless, they are two widely used methods for deriving performance, especially efficiency. There are lessons from this thesis, especially on the cost structure, mode differences, and ownership effects. First, traffic density and scale affect different performance dimensions (i.e., cost efficiency, service effectiveness and cost effectiveness) in different ways. Second, mode affects different performance dimensions in different ways. Third, Returns to Density (RTD) and Returns to Scale (RTS) vary between over-ground, monorail, and under-ground. Fourth, private firms are profit-maximising entities but not necessarily cost-efficiency maximisers. Fifth, measuring all the performance dimensions and interpreting the results relative to each other is essential. These findings are essential for firms, regulators, and funders. Given the interest in the empirical performance of private urban rail firms, we suggest future research investigate how they perform in cost efficiency, service effectiveness and cost effectiveness in other regions. We also hope that future empirical research will clarify the RTD and RTS of urban rail modes.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

CED	Cost Elasticity with respect to Density
CES	Cost Elasticity with respect to Scale
CRS	Constant Returns to Scale
DRS	Decreasing Returns to Scale
IRS	Increasing Returns to Scale
RTD	Returns to Density
RTS	Returns to Scale
VRS	Variable Returns to Scale
w.r.t	with respect to

Chapter 1 Introduction

Rail services are a form of transportation that utilises a fixed track system, where trains travel on rails to convey passengers and cargo. Rail services are classified into two types: freight rail and passenger rail. Freight rail is predominantly used to transport long-distance goods, such as raw materials, finished products, and heavy equipment. It is a necessary form of transportation for enterprises, industries, and supply chains that rely on the practical and reliable flow of goods. On the other hand, passenger rail is mainly used to move people over long and short distances, usually between cities and within urban.

Passenger rail services can be classified into two distinct categories: intercity rail and urban rail. Intercity rail services, such as the Eurostar in Europe, transport people over extended distances between cities. These rail services operate in regions where cities are geographically separated. Common features include spacious seating, access to refreshments, and even the chance to spend the night if the journey is lengthy. In contrast, urban rail services are intended to transport people to and from their places of employment and other locations within urban or suburban areas. Typical urban rail services include subways, light rail, commuter rail, and elevated train systems. They commonly run during the busiest times of the day, whereas significantly fewer trains operate outside those times.

Urban rail services provide various advantages over other means of transportation, including shorter travel times, less traffic congestion, and lower pollutants (Xiaoqiang, 2020). They are also more reliable than buses or cars since they run on fixed tracks and are less likely to be disrupted by traffic or accidents.

The cost of operating an urban rail system can vary depending on several factors, including the system's size, complexity, and vehicle type. Labour, energy, and maintenance and repair are the primary cost generators for urban rail. Labour can account for a substantial portion of the operating costs, mainly if the system is operational 24 hours a day or provides frequent services. Energy may also be significant, especially for systems that rely on fossil fuels or outdated, less efficient equipment. Maintenance and repair are critical for keeping trains and equipment in excellent working order, and they can be high, especially for older systems or those with a large fleet of cars.

Running urban rail services can be costly; in some contexts, it requires subsidy. Therefore, ensuring that costs are kept in line is vital as it affects government expenditure and passenger fares. Even where governments do not subsidise to a large extent, like in Japan, competitive or regulatory pressure would suggest that costs must be efficient. This condition motivates studies that understand the structure of costs and whether firms are operating efficiently. The findings of these studies are essential for firms, regulators, funders, and users.

An urban rail service's performance, including cost performance, can be measured by analysing its historical data or by comparing its data against that of others. Let us call the former a *self-assessment* and the latter a *peer comparison*.

Self-assessment is a relatively straightforward exercise as it is easy to access internal data. Looking at a firm's productivity over time, one can tell how the firm has been performing. However, self-assessment has two shortcomings. One, self-assessment does not tell where a firm sits in the industry or whether its productivity is in tandem with those of other firms in the industry average. Two, self-assessment does not tell the firm's productivity growth is in tandem with those of other firms in the industry.

Peer comparison can be applied to address these shortcomings. However, implementing performance measurement on urban rail services through peer comparison faces two intriguing issues: the comparability of peers and the variation in previous findings.

Parks et al. (2010, p. 2) pointed out that "many believe that no two transit agencies are alike". For example, Tsamboulas (2006) found that public-owned operators were less efficient and effective than privately owned, profit-oriented operators. Besides that, performance is also found to be influenced by other factors. For instance, the performance of an urban rail service can vary by operating in a different *population density* (Tsai et al., 2015).

Additionally, previous studies produced differing findings on how exogenous factors affect urban rail performances — so much so that one contradicted another. For example, Jain, Cullinane, and Cullinane (2008) found private operators were the most efficient, followed by corporate and public, respectively. On the contrary, Min, Ahn, and Lambert (2017) concluded ownership influence on efficiency was insignificant. These differences may put one in a dilemma in choosing the findings to rely on.

Over time, there has been significant variation in the definitions of firm performance, and there have been limited efforts to establish systematic connections between these definitions across different studies (Perry et al., 1988). In addition, "some of the reasons for the absence of consistent and cumulative research results are methodological" (Perry et al., 1988, p. 138). These "methodological" causes include different samples, periods, and analytical methodologies. With these points in mind, this thesis adapted performance definitions (i.e., cost efficiency, service effectiveness, and cost effectiveness) introduced by Fielding et al. (1985), applied two different approaches (i.e., trans-log cost function and DEA-Tobit regression), and analysed the effects of some selected exogenous factors (i.e., mode, density, scale, and ownership). More details will be elaborated when we discuss the literature review (Chapter 2) and methodology (Chapter 3).

The empirical work presented in this thesis centres on urban rail in Japan as its primary focus. The market for urban rail in Japan is one of a kind. "Japanese passenger railways are financially healthy and performing well in metropolitan areas" (Mizutani, 2014, p. 4). This situation contrasts with the case in many other countries. There are private, public, and quasi-public operators participating in this market. Most operators are also the owners of the rail infrastructure. A select few are responsible for the operation of the rail infrastructure alone, while another select few oversee the rail services alone. In addition, Japan's regulatory climate is quite distinctive compared to any other country or region in the world (further details will be elaborated in Chapter 4). Nevertheless, there can be lessons for other countries, especially on the cost structure, mode differences, and ownership effects.

This thesis comprises three interrelated research studies. Research Study 1 (Chapter 5) aims to understand the cost structure of each urban rail mode in Japan and determine whether there is any significant difference between them. The research objectives are to:

a. determine whether operating costs vary between modes and whether there is a significant difference between them,
b. determine whether economies of density characteristics vary between modes and whether there is a significant difference between them, and
c. determine whether economies of scale characteristics vary between modes and whether there is a significant difference between them.

Research Study 2 (Chapter 6) explores the ownership effect on cost efficiency in the Japanese urban rail sector. The research objectives are to:

a. determine whether adding the ownership variable into Research Study 1's trans-log cost function model does not materially change the coefficients elsewhere,
b. explore whether different methods (i.e., trans-log cost function and DEA-Tobit Regression) would yield similar results, and
c. determine whether private firms are more cost-efficient than other firms.

Research Study 3 (Chapter 7) aims to explore further the ownership effect on each performance dimension (i.e., cost efficiency, service effectiveness and cost effectiveness) in the Japanese urban rail sector and investigate the density, scale, and mode effects on each performance dimension. The research objectives are to:

a. determine whether private firms are more service effective than other firms,
b. determine whether private firms are more cost-effective than other firms,
c. compare and evaluate private firms' performance in cost efficiency, service effectiveness, and cost effectiveness, and
d. compare and evaluate how density, scale, and mode affect cost efficiency, service effectiveness, and cost effectiveness.

In Research Study 3, the private firms' cost efficiency from Research Study 2 is used to compare and evaluate the private firms' service effectiveness and cost effectiveness.

The rest of this thesis is laid out as follows. Chapter 2 reviews the literature. We organised the literature into two sections in this chapter. The first is the performance of urban rail modes, while the second is that of private firms. We evaluated prior studies on urban rail performance in the first section. We also discussed the advantages of understanding the cost structure. The second section expanded on the theoretical expectations for private firm performance. We also looked at existing research on private firms' performance compared to other firms (including public firms).

Chapter 3 elaborates on the methodology. We will elucidate the research studies' methods based on our research aims. As mentioned, there are three primary research aims and a separate study for every aim. These studies were conducted in stages since each study has a methodological connection. For example, the model specified in the first research study was employed in the second. We will also refer to some findings from the preceding study when discussing the methodologies used in the second and third research studies.

Chapter 4 looks at the Urban Rail Environment and Data in Japan. We will start by discussing eight regulatory aspects in Japan. The principles and strategies commonly employed in the industry include the self-sufficiency principle, diversification strategy, subsidies, market entry and exit, licences, fare, competition, and regulation. In the following part of this chapter, we will describe the data sources used in each research project and the variables that were investigated. After that, we will discuss the correlation between the Mode variable and the Ownership variable and whether this will affect the research studies we will conduct.

Chapter 5 discusses the results and findings of Research Study 1. We started by giving a synthesis of the results from simple ratios, which are non-econometric methods. After that, we discussed the operating costs, Returns to Density (RTD), and Returns to Scale (RTS) based on the trans-log cost function, an econometric approach. Then, we discussed the differences between the results from simple ratios and the trans-log cost function. This chapter's discussion continues with several policy implications.

Chapter 6 discusses the results and findings of Research Study 2. Firstly, we compared and evaluated the results from the trans-log cost function model used in Research Study 1 against those from the trans-log cost function model used in Research Study 2. We then compared and evaluated the results from the DEA-Tobit regression model against those from the trans-log cost function model used in Research Study 2. This evaluation is followed by a discussion on private firms' performance in cost, cost efficiency and technical efficiency in the Japanese urban rail sector. The subsequent discourse in this chapter encompasses several plausible reasons for our findings.

Chapter 7 discusses the results and findings of Research Study 3. We began by comparing the regression results for all performance dimensions: cost efficiency, service effectiveness, and cost effectiveness. Here, we investigated the effects of ownership, traffic density, scale, mode, time, and population density on cost efficiency, service effectiveness, and cost effectiveness. In general, cost efficiency is the relationship between service input and service output;

service effectiveness is the relationship between service output and service consumption; and cost effectiveness is the relationship between service input and service consumption. We then concentrated on the performance of Japanese private urban rail firms in terms of cost efficiency, service effectiveness, and cost effectiveness. This chapter's further discussion presents numerous reasons for our findings.

Chapter 8 concludes this thesis.

Chapter 2 Literature Review

In this chapter, we divided the literature into two sections. First is the performance of urban rail modes, and second is the performance of private firms. In the first section, we reviewed previous studies on urban rail performance. We also explained the benefits of knowing the cost structure. In the second section, we elaborated on the theoretical expectations of private firms' performance. We also reviewed previous studies on private firms' performance relative to other firms (including public firms).

Along the way, we picked up gaps that motivated us to conduct three research studies. For completeness and clarity, we restated our research aims with objectives at the end of the first section, in the middle of the second section, and at the end of the second section — where the gaps are found. We also mentioned these aims and objectives in the relevant chapters for convenience.

2.1 The Performance of Urban Rail Modes

There are numerous studies on the performance of rail services. These studies include long-haul services as well as short-haul services. Long-haul is inter-state services, while short-haul is urban services. There are situations where inter-state services cut across a large metropolitan area. They may have two stops or more in that area and may indirectly serve the urban commuters. However, this is not the nature of their services. The purpose of their existence is to serve the inter-state commuters. The inter-state services often consist of passenger and cargo transportation, whereas the urban rail services mainly transport passengers. Combining inter-state and urban rail services in a study may cause complications as each has different characteristics. This section of the literature review, therefore, focuses on urban rails. At times, we included other studies we found relevant, especially in the next section — when we discuss the performance of private firms.

One concern with the urban rail services is that even after separating them from the long-haul services, they further consist of different rail modes such as over-ground, monorail, and under-ground. While some studies on urban rail performance mentioned the rail modes[1] being evaluated, others did not.

Table 1 on page 11 lists 14 studies on urban rail performance from 1997 to 2018. We checked whether these studies had addressed mode differences. We say a study has implemented mode separation when it runs separate analyses for different modes. We say a study has implemented mode recognition when the sample is kept together, but mode dummies are included. We say a study has implemented a mode definition when it includes mode definitions. As shown under the Mode Separation column, none of these studies separated rail modes before making their respective analyses. As shown under the Mode Recognition column, some of these studies recognised mode differences in their respective analyses. Of the five studies that implemented mode recognition, only two — Savage (1997) and Min et al. (2017) — treated mode differences more seriously by including mode definitions.

Mode difference was recognised as early as 1997 by Savage (1997), but many studies did not follow suit after that. Studies like Babalik-Sutcliffe (2002) and Walter (2011) encompassed some urban rail modes but did not recognise mode differences. Furthermore, studies like Sekiguchi et al. (2010) which coined 'urban railway'[2], did not even mention the modes involved, let alone recognise mode difference.

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[1] The categorisation of urban rail services varies from one region to another. For example, in the United States, urban rail services are categorised into five: heavy rail (HR), light rail (LR), monorail (MR), streetcar rail (SR), and commuter rail (CR). On the other hand, in Japan, urban rail services are generally categorised into three: over-ground (OG), monorail (MR), and under-ground (UG).

[2] Companies performing the functions of a railway and operating rail cars on fixed rail guides/tracks; serving urban areas with population of 300,000 or more.

Stating and recognising mode differences has not been a standard practice.

Four of the five studies that recognised mode difference focused on the production aspect — albeit in varying ways. These four are Graham (2008), Ingvardson and Nielsen (2018), Min et al. (2017) and Tsai et al. (2015). Only one, Savage (1997), focused on the costs aspect. Savage (1997) conducted his study more than two decades ago. We are unaware of any study that recognised urban rail mode difference when evaluating the cost structure aspects since then — especially in extracting Cost Elasticity w.r.t Density (CED) and Cost Elasticity w.r.t Scale (CES) for each rail mode[3].

[3] More about cost elasticity w.r.t density and scale will be discussed in Chapter 3: Methodology.

Table 1. Studies on urban rail performance

Author(s)	*Mode Separation*[4]	*Mode Recognition*[5]	*Mode Definition*[6]	*Mode Evaluated*	*Region*	*Method*	*Remark*
Babalik-Sutcliffe (2002)	No	No	No	Metros & light rails	USA, Canada, & UK.	Case Study	The term used: urban rail systems
Graham (2008)	No	Yes	No	Metro, light rail, & suburban rail	Worldwide	DEA & Trans-log Production Function	
Ingvardson and Nielsen (2018)	No	Yes	No	Metro, Suburban rail, light rail, & bus	Europe	Multiple Regression & Factor Analysis	Some cities operate several modes; some do not.

[4] Separating rail modes before evaluating operators
[5] Addressing mode difference through the use of variables such as dummies
[6] Providing definition for each rail mode

Author(s)	*Mode Separation*[4]	*Mode Recognition*[5]	*Mode Definition*[6]	*Mode Evaluated*	*Region*	*Method*	*Remark*
Karlaftis (2004)	No	No	No	No clear breakdown or explanation	USA	DEA	The term used: urban transit systems
Min et al. (2017)	No	Yes	Inferred from FTA definitions	Light rail, streetcar, bus, etc.	USA	DEA & Tobit Regression	The term used: mass transit. Some DMUs operate in several modes.
Mizutani (2004)	No	No	No	No clear breakdown or explanation	Japan	Trans-log Cost Function	The term used: urban railway
Mizutani and Shoji (2004)	No	No	No	No clear breakdown or explanation	Japan	Trans-log Cost Function	The term used: rapid transit railway

Author(s)	*Mode Separation*[4]	*Mode Recognition*[5]	*Mode Definition*[6]	*Mode Evaluated*	*Region*	*Method*	*Remark*
Mizutani et al. (2009)	No	No	No	No clear breakdown or explanation	Japan	Cost function	The term used: urban railway
Novaes (2001)	No	No	No	No clear breakdown or explanation	Worldwide	DEA	The term used: rapid transit systems
Savage (1997)	No	Yes	Yes	Heavy rail & light rail	USA	Trans-log Cost Function	

Author(s)	*Mode Separation*[4]	*Mode Recognition*[5]	*Mode Definition*[6]	*Mode Evaluated*	*Region*	*Method*	*Remark*
Sekiguchi et al. (2010)	No	No	No	No clear breakdown or explanation	Japan	DEA	The term used: urban railway[7]
Tsai et al. (2015)	No	Yes	No	Heavy rail, rapid rail, & commuter rail	Worldwide	DEA & Tobit Regression	Only one dummy variable (heavy rail) was used.
Tsamboulas (2006)	No	No	No	No clear breakdown or explanation	Europe	DEA & Tobit Regression	

[7] Companies performing the functions of a railway and operating rail cars on fixed rail guides/tracks; serving urban areas with population of 300,000 or more.

Author(s)	*Mode Separation*[4]	*Mode Recognition*[5]	*Mode Definition*[6]	*Mode Evaluated*	*Region*	*Method*	*Remark*
Walter (2011)	No	No	No	Metro, light rail, tram, & bus	Germany	Cost Function	Used 'railcar utilisation rate' to address rail influence on performance; but did not specify rail mode.

With the availability of relevant data on Japanese urban rail services, we are motivated to understand the cost structure of each urban rail mode[8] in Japan and determine whether there is any significant difference between them. The cost structure is defined in this thesis to relate operating cost levels, economies of density, and economies of scale. Knowing these components carries three key benefits.

One, if operating costs differ between urban rail modes, it is necessary to recognise that different rail modes would naturally require different financial commitments. Operating and infrastructure construction costs could be considered when selecting which rail mode to construct. This combination enables policymakers to decide which mode to construct when considering a new urban rail project — particularly from the operating costs aspect of Cost Benefit Analysis (CBA).

Two, if economies of density are different between urban rail modes, different urban rail modes will experience different impacts on costs when the output level is increased or decreased. An output increase may result in higher operating costs for one rail mode but lesser additional operating costs for another. It may eventually result in higher average operating costs for the former. With this information, policymakers can consider and specify the expected output level from an urban rail service. Not only that, a realistic amount of incentive and subsidy can also be allocated.

Three, if economies of scale are different between urban rail modes, different urban rail modes will experience different impact on costs when traffic and network length is increased or decreased. Just like output increment, a network expansion may result in higher additional operating costs for one rail mode and may eventually result in a higher average operating cost. This information will help policymakers decide on expanding the current urban rail network.

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[8] Over-ground, monorail, and under-ground.

Therefore, in Research Study 1 (Chapter 5), we aim to understand the cost structure of each urban rail mode in Japan and determine whether there is any significant difference between them. In doing so, we will

a. determine whether operating costs vary between modes and whether there is a significant difference between them,
b. determine whether economies of density characteristics vary between modes and whether there is a significant difference between them, and
c. determine whether economies of scale characteristics vary between modes and whether there is a significant difference between them.

2.2 The Performance of Private Firms

There are reasons to believe that private firms are better positioned than public firms in profitability[9]. The first reason is property rights assignment. The assignment of property rights to private entities allows ownership to be traded. Private owners' goal of gaining benefits[10] from their investment puts firm managers under constant pressure to perform well. Private owners may change the firm's management if poor performance affects profitability. Alternatively, they may sell their ownership to new owners, who would likely set up a new management team to improve performance[11]. Hence, private firms will strive to maximise profit in such an environment. "The property rights theory of the firm suggests that public enterprises should perform less efficiently and profitable than private enterprises" (Boardman & Vining, 1989, p. 1).

The second reason is the principal-agent problem. Although the problem exists in both public and private firms' environments, it is more

[9] We will explain how profitability leads to cost efficiency and service effectiveness in later paragraphs.
[10] Such as dividends and higher share prices.
[11] We know that it will be challenging to impose changes under multiple owners. However, our aim in this paragraph is to present the basic idea of the theory.

severe in the former's due to the challenge of implementing performance-based pay systems (Rees, 1985). Moreover, there are layers of principal-agent problems under public ownership. Figure 1 on page 19 illustrates principal-agent layers that typically exist under public ownership. Conceptually, citizens are owners of public firms. They are represented by a politician-appointed Minister with the relevant portfolio. It is the first layer in which citizens act as the principal and the minister as the agent. The minister delegates his authority to civil servants to monitor the performance of public firms. It is the second layer in which the minister acts as the principal, and civil servants act as the agent. Civil servants interact with firm managers about the firm's performance. The third layer is where civil servants act as the principal and firm managers act as the agent. Under a typical bureaucratic environment, communication is relayed through these principal-agent layers.

More so within each party, there exists bounded rationality — which is conceptualised as "a kind of rational behaviour that is compatible with the access to information and the computational capacities that are possessed by organisms, including man, in the kinds of environments in which such organisms exist" Simon (1955, p. 99). This cognitive limitation is coupled with short-termism, which surfaces from the political cycle and career promotion. This situation makes asymmetry issues severe under public ownership — causing inaccurate or delayed information and response on the performance of public firms.

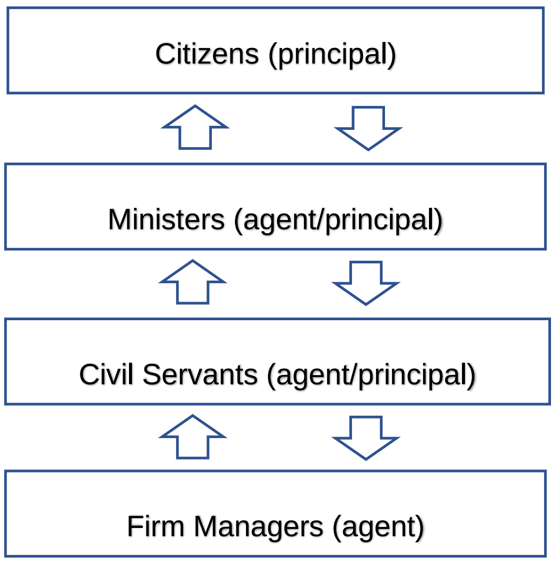

Figure 1. Typical agents under public ownership

The third reason is the differing goals between private and public firms. While private firms strive for profit maximisation, public firms prioritise social welfare, although they may be given a profit target amongst other targets. These three reasons suggest private firms are better positioned to generate profit than public firms.

On another note, there is a debate on the importance of ownership in the presence of competition. For example, Caves and Christensen (1980) suggested that the most crucial factor in determining the success of Canadian railroads is not the type of ownership but rather competition. However, Vining and Boardman (1992) later disputed that Caves and Christensen (1980) investigated a duopoly market lacking a competitive environment. Vining and Boardman (1992) further showed that: (1) ownership is both theoretically and empirically significant; (2) most of the evidence purporting to demonstrate the "primacy of competition versus ownership" or "no difference in efficiency" does not and cannot do so convincingly; and (3) new empirical evidence using Canadian data confirms the significance of ownership.

2.2.1 Performance Measurement Framework for Transit Sector

As stated in one of the preceding paragraphs, private firms aim to maximise profit. Profit maximisation can be achieved by maximising revenue and minimising cost. Holding product and input prices constant, maximising output and minimising input can maximise profit. It leads to the basic concept of efficiency — "the relationship between resource input[12] and produced output[13]" (Fielding et al., 1985, p. 73). However, this concept needs adjustments when measuring efficiency in the transit sector. It is because transit outputs are non-storable as opposed to factory outputs. Kamaruddin (2012, p. 10) explained non-storable outputs as follows:

"However, different from factory products, transport services are non-storable. A factory product, say a car, can be stored in a warehouse until there is an order from a customer. But a transport service, say a flight from Heathrow to Paris, cannot be put on hold until all the seats are sold (or occupied). This is because transport services are schedule driven. When the time comes, an aeroplane must fly regardless of how many passengers are on board. Some of the seats are going to be occupied, and some are not. The occupied seats are regarded as *services consumed* while the empty ones are regarded as *services wasted*."

[12] Also referred as service input.
[13] Also referred as service output.

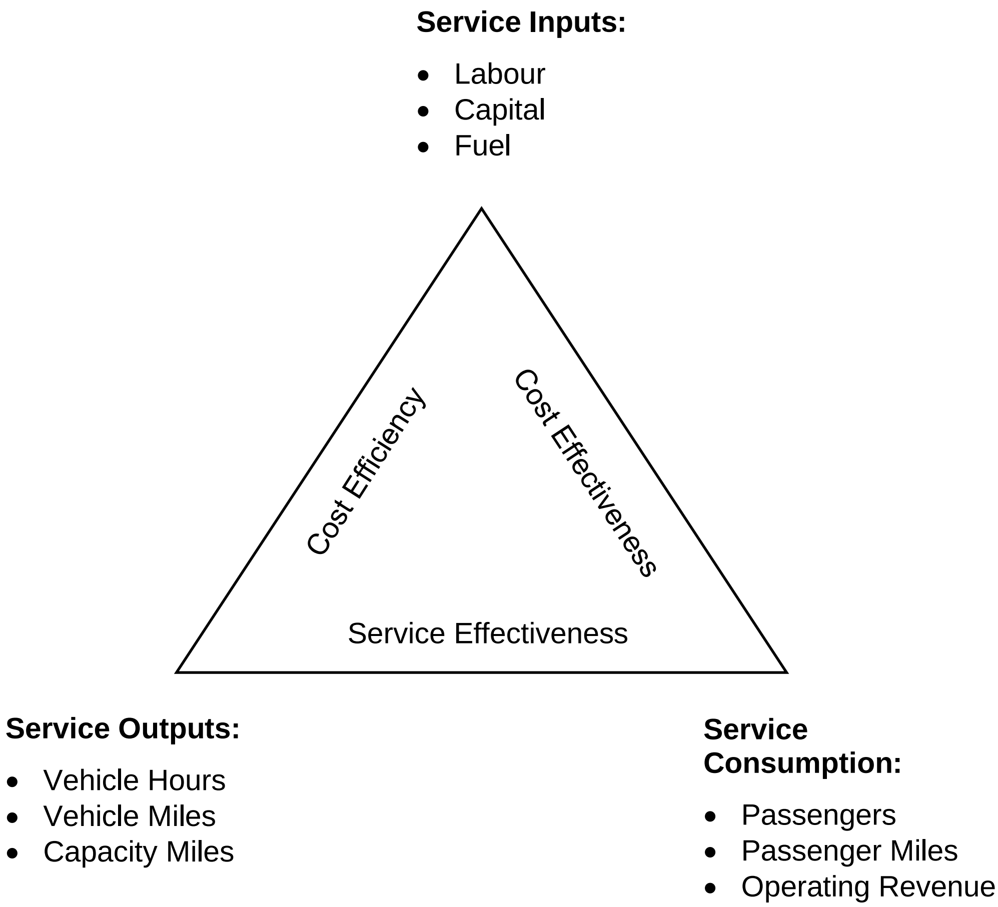

Figure 2. Framework for transit performance. Source: Fielding et al. (1985)

Fielding et al. (1985) presented a performance measurement framework for the transit sector (Figure 2 on page 21). In this framework, there are three main variables under consideration. The first one is service inputs like labour, capital, and fuel. The second one is service outputs like vehicle hours, vehicle miles, and capacity miles[14]. The third one is service consumption, such as passengers, passenger miles, and operating revenue. The relationship between service input and service output is called cost efficiency. The relationship between service output and service consumption is called service effectiveness. The relationship between service input and

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[14] Such as seat-km.

service consumption is called cost effectiveness. In the absence of cost data, technical efficiency[15] (as opposed to cost efficiency) and technical effectiveness[16] (as opposed to cost effectiveness) could be used — as exercised by Lan and Lin (2003). Fielding et al. (1985) treated the abovementioned relationships as ratio variables. In this research, we used regression equations. More details will be discussed in Chapter 3: Methodology.

The framework has been applied in several pieces of research about rail performance evaluation. Karlaftis (2004) referred to the framework when evaluating the efficiency and effectiveness of urban transit systems (256 US transit systems). Lan and Lin (2006) applied the framework when examining the technical efficiency and service effectiveness of 39 worldwide railway systems. Yu and Lin (2008) did the same when evaluating the technical efficiency and service effectiveness of 20 selected railway firms worldwide in 2002. Other researchers that utilised the framework include Currie et al. (2011), Tsai et al. (2015), and Kleinová (2016).

Under this framework, profit can be maximised by maximising cost effectiveness (i.e., maximising service consumption and minimising service input). Assuming regulation constrains service output[17], profit can be maximised by maximising cost efficiency (i.e., minimising service input) and service effectiveness (i.e., maximising service consumption). Furthermore, assuming the regulation constrains output prices[18], service effectiveness can be maximised by maximising

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[15] The relationship between service input and service output in their respective units such as the number of labours for resource input and the amount of train journey (car-km) for produced output.

[16] The relationship between service input and service consumption in their respective units such as the number of labours for resource input and the amount of passenger journey (passenger-km) for service consumption.

[17] Firms are expected to provide reliable routine services which in turn, limits their service output adjustment.

[18] Ticket prices are typically set with the regulator’s agreement. In some regions like Japan, price caps are imposed. Any adjustment beyond

output consumed (i.e., passengers or passenger miles). With this framework in mind, privatisation seems beneficial to the transit market. Better cost efficiency, service effectiveness, and cost effectiveness are to be expected from privatisation. Figure 3 on page 23 depicts the theoretical expectations of private firms' performance.

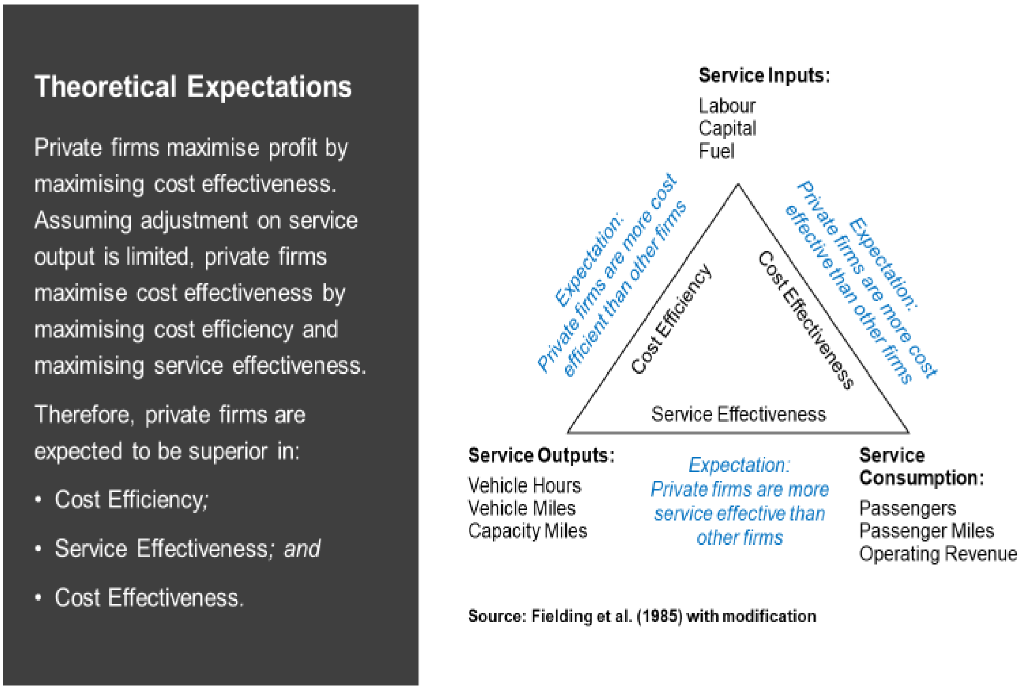

Figure 3. Theoretical Expectations of Private Firms' Performance

2.2.2 Expected Private Firms' Performance in a Monopolistic Market and a Perfectly Competitive Market

Although a private firm strives to maximise profit, its performance on cost efficiency and service effectiveness are expected to differ in a monopolistic market compared to a perfectly competitive market. For simplicity, we will use an unregulated environment[19] to explain how a

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price caps needs the regulator’s approval. More about price caps in Japan will be explained later.

[19] Usually, urban rail market is regulated but the intensity of regulation is different from one region to another. To make the scenario equal between a perfectly competitive market and a monopolistic market, we set aside government intervention.

private firm would perform on cost efficiency and service effectiveness in both markets — except that the service output is constrained. Here, we assumed urban operators could not freely adjust their service output[20]. Constraining service output has been practised in the literature, such as Kerstens (1996), Lan and Lin (2003) and Tsai et al. (2015).

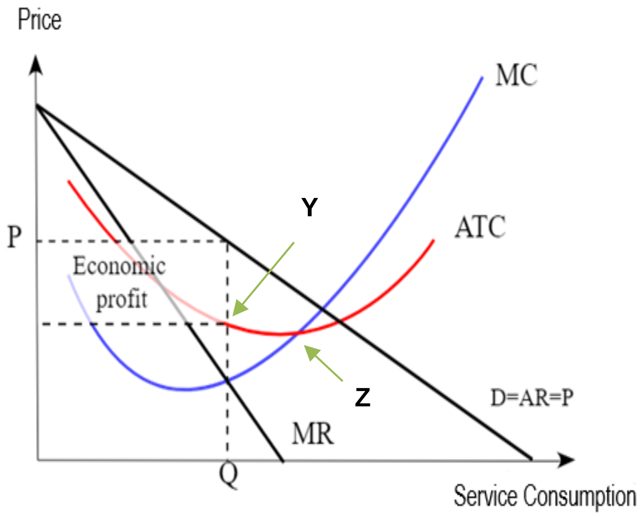
When their service output is constrained, the operators' decision is limited to adjusting ticket prices to increase or decrease service consumption in pursuit of profit maximisation. We also expect operating costs to increase when service consumption rises. For example, more personnel are needed to handle more station commuters.

Usually, urban rail ticket prices are subject to price cap regulation. Ticket prices are capped because the urban rail market is not perfectly competitive. If the market is perfectly competitive, price capping is not needed. To make the scenario equal between a perfectly competitive market and a monopolistic market, we set aside government intervention on price.

Monopolistic Market

Figure 4 on page 25 illustrates profit maximising conditions for a firm in a monopoly market. To maximise profit, the monopoly firm will find that it is best to operate at point Y when its average total cost (ATC) is still downward sloping.

[20] Urban rail operation is expected to meet the minimum service level or frequency. The operation is also limited to maximum traffic density.



P = price set

Q = services consumed (e.g., passenger miles)

Figure 4. Profit maximising conditions for a firm in a monopoly market.

Suppose the firm does not have enough service consumption to maximise profit (i.e. on the left side of point Q in Figure 4 on page 25). It may reduce ticket prices to induce service consumption. When service consumption increases, the new combination of revenue and cost will result in a better profit. It goes on until the profit is maximised. In this situation, service effectiveness increases[21] compared to the previous one. However, cost efficiency[22] decreases resulting from increased operating costs.

On the other hand, if the firm finds reducing service consumption can maximise profit (i.e. on the right side of point *Q* in Figure 4 on page 25), it may increase ticket prices. Service consumption will decrease, and the new combination of revenue and cost will result in a better profit. In this case, service effectiveness decreases following reduced

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[21] Bear in mind that we hold the service output constant, and service effectiveness is the relationship between service output and service consumption such as service consumption divided by service output.

[22] Bear in mind that we hold the service output constant, and cost efficiency is the relationship between operating costs and service output such as service output divided by operating costs.

service consumption, and cost efficiency increases resulting from decreased operating cost.

Note that the monopoly firm is not operating at point Z, where marginal cost (MC) equals the lowest average total cost (ATC) — when productive efficiency is achieved. Therefore, we can say that a firm in a monopolistic market does not aim to be productively efficient even though it has a profit maximising goal.

Perfectly Competitive Market

The situation is different for a private firm that operates in a perfectly competitive[23] market. The firm is a price taker. To maximise profit, it must find ways to reduce operating costs and increase service consumption — it does not have control over ticket prices. Figure 5 on page 27 illustrates the profit maximisation condition for a private firm in a perfectly competitive market. The firm survives when the marginal cost (MC) equals the lowest average total cost (ATC), making it productively efficient. At the exact moment, its average total cost (ATC) equals average revenue (AR), resulting in zero profit[24].

[23] We are aware that perfect competition is ideal and implausible in the transit market due to some limitations. For example, there can only be one train at one route stop at one time. However, we illustrate perfect competition for conceptual understanding.

[24] Operating at different points results in losses since the average total cost is more than the average revenue.

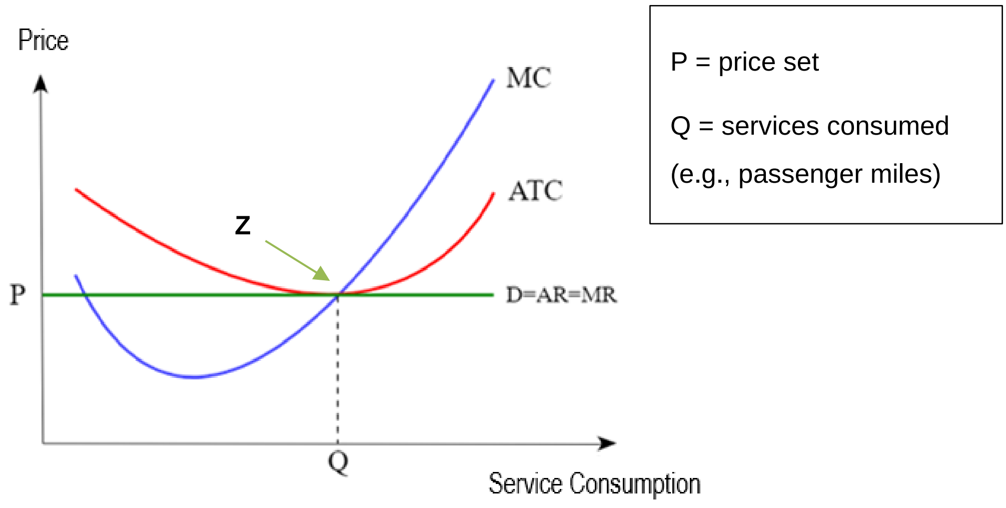

Figure 5. Profit maximising conditions for a firm in a perfectly competitive market.

Suppose the firm does not have enough service consumption to survive (i.e., on the left side of point Q in Figure 5 on 27). It can increase advertising and promotion to induce more service consumption. Service consumption will increase, and the new combination of revenue and cost will enable the firm to survive in the market (at point Q). In this case, cost efficiency[25] will decrease, resulting from increased operating costs (advertising and promotion). On the other hand, service effectiveness[26] will increase following the increase in service consumption — compared to its previous performance.

If the firm has so much service consumption that it finds its average cost more than its average revenue, which results in losses (i.e. on the right side of point *Q* in Figure 5 on page 27), it can decrease

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[25] Bear in mind that we hold the service output constant, and cost efficiency is the relationship between operating costs and service output such as service output divided by operating costs.

[26] Bear in mind that we hold the service output constant, and service effectiveness is the relationship between service output and service consumption such as service consumption divided by service output.

advertising and promotion. Service consumption may then reduce, and the new combination of revenue and cost will result in zero loss (at point Q, where the average cost equals the average revenue). In this case, cost efficiency will increase following a decrease in cost, but service effectiveness will decrease[27] following a reduction in service consumption compared to its previous performance. The process is dynamic in a perfectly competitive market because firms strive to increase cost efficiency and service effectiveness.

Also, note that the firm operates at point Z, where marginal cost (MC) equals the lowest average total cost (ATC) — when productive efficiency is achieved. Therefore, we can say that a firm in a perfectly competitive market aims to be productively efficient on top of having a profit maximising goal (or loss-minimising goal). However, as we stated earlier, a firm in a monopolistic market does not aim to be productively efficient even though it has a profit maximising goal. Given this difference, we expect a firm's performance on cost efficiency and service effectiveness to differ in a monopolistic market compared to a perfectly competitive market.

Urban Rail Market

The urban rail market is usually oligopolistic, but the degree of oligopoly varies from one region to another. Because we expect private firms’ cost efficiency and service effectiveness performance to differ in a monopolistic market compared to a perfectly competitive market, we expect private firms’ cost efficiency and service effectiveness performance to also vary between oligopolistic markets and regions. One caveat is that regulation is imposed at varying degrees in different regions (Nash & Smith, 2021). Although it may reduce the differences in private firms' cost efficiency and service effectiveness between monopolistic and perfectly competitive markets, the efficacy of regulation between markets may also differ. In

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[27] Assuming the regulation constrains service outputs.

their study, Smith et al. (2018) employed a sample of 17 European railways from 2002 to 2010. The study revealed that the existence of robust economic regulations is associated with reduced costs of the rail system. Nonetheless, the aforementioned cost reduction is solely observable when combined with vertical separation.

Vertical separation is not ubiquitous across all rail markets. According to Nash and Smith (2021), the rail markets in North America and Japan exhibit a vertically integrated structure. For this reason, we intend to choose only one urban rail market to study. By doing so, we will have consistent expectations of private firms' cost efficiency and service effectiveness (i.e., holding market structure and regulatory conditions constant).

Having explained the theoretical concept, we are motivated to contextualise it within the Japanese urban rail market. We will evaluate the performance of private firms on cost efficiency, service effectiveness, and cost effectiveness relative to other firms[28].

2.2.3 Cost Efficiency

Many public firms worldwide have been converted to private firms since the late 1970s. This ownership conversion is widely known as privatisation. It started in Great Britain and spread to countries worldwide (Bortolotti et al., 2004; Karlaftis, 2008; Young, 1987). The privatisation exercise includes bus, railway, and urban rail firms in the land transport sector.

Since there are only a handful of studies on the ownership effect on the cost efficiency, service effectiveness, and cost effectiveness of urban rail services, we expanded the scope of the literature review to the land transport sector. We do not include air and maritime transport sectors because of their market uniqueness.

[28] Quasi-public and public firms.

Many empirical studies have been conducted on private firms' efficiency[29] in the land transport sector after privatisation. It implies the importance of ownership concerning efficiency in the literature. However, not all define efficiency as the relationship between service inputs and service outputs, as shown in Figure 2 on page 21.

The first example is Jain et al. (2008), who looked at 15 urban rail transit systems worldwide to assess the connection between ownership structure and technical efficiency. They used labour, capital, and line (network length) as service input and car-kilometre and passenger-trip as service output to measure technical efficiency. While *car-kilometre* is a form of service output, *passenger-trip* is a form of service consumption. Combining them is impractical because *passenger-trip* is dependent on *car-kilometre*. *Passenger trip* is zero when *car-kilometre* is zero, but *car-kilometre* is not necessarily zero when *passenger-trip* is zero. In other words, passengers could not travel when the train is not moving, but there could be no passengers on board when the train is moving.

The second example is Min et al. (2017), who looked at 515 mass transit agencies in the USA to identify factors influencing efficiency[30]. Their service inputs are *operating expenses*, *funds*, *passenger trips*, and *passenger miles*, while their service outputs are *fare-revenue*, *vehicle miles*, and *vehicle hours*. Note that *operating expenses* are a form of service input, *vehicle miles* and *vehicle hours* are service output, and *passenger trips* and *passenger miles* are forms of service consumption. As explained in the previous example, combining them is impractical.

The third example is Costa et al. (2021). Their service inputs are *operating costs*, *asset value*, and *liabilities*[31], while their service

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[29] This can either be cost efficiency or technical efficiency. We will separate them in later paragraphs.
[30] The authors mixed input cost and input units.
[31] as a percentage of asset

outputs are *revenue*[32] and *earnings*[33]. R*evenue* is a form of service consumption, and "inputs do not necessarily vary very systematically" with such a demand-related output measure (Kerstens, 1996, p. 439; Roy & Yvrande-Billon, 2007). Filippini and Maggi (1993, p. 205) stated that "it is not evident why cost depends on the number of passengers on a train — running an empty train is not cheaper than running a full one". Therefore, the efficiency scores might be misleading (Scheffler et al., 2013). From our perspective, the relationship between *revenue* and *operating costs* reflects cost effectiveness instead of efficiency.

Perry et al. (1988, p. 137) stated that "there was considerable variation of form-performance definitions over time and few attempts to relate them systematically from study to study". To address this, we evaluated findings from studies that adopt the efficiency definition by Fielding et al. (1985). Still, there seems to be no conclusive answer to the ownership effect on efficiency in the land transport sector. The findings are as follows.

For bus services, Mizutani and Urakami (2003) found that private firms are more efficient than public firms in Japan. They stated private firms received limited subsidies and had to be self-sufficient through fare-revenue collection. On the other hand, public firms continued receiving subsidies despite having higher employee salaries than private firms. Ottoz et al. (2009) also found private firms more efficient than public firms in Italy, but they did not explain why. In contrast, Scheffler et al. (2013) found ownership had no impact on the efficiency of German bus firms. They pointed out that ownership did not influence efficiency in a monopoly market, as seen by Megginson and Netter (2001), and in a regulated non-competitive market, as found by Jørgensen et al. (1997). Perry et al. (1988) reviewed 20 international studies regarding the efficiency of private firms and found that some studies concluded

[32] from tickets

[33] earnings before interest, taxes, depreciation, and amortisations — as a percentage of revenue

that private firms are more efficient than public firms, while others concluded otherwise. They stated that "some of the reasons for the absence of consistent and cumulative research results are methodological", including different samples, periods, and analytical methods (Perry et al., 1988, p. 138).

For railway services, Filippini and Maggi (1993) found that ownership does not affect efficiency in Switzerland. They concluded that in "a federal state with a complex ownership and subsidy structure, private versus public ownership issues are probably of less relevance than questions relating to the adequate federal distribution of tasks and funds" (Filippini & Maggi, 1993, p. 212). In contrast, Cowie (1999) found private firms more efficient than public firms in Switzerland. He explained that private firms faced fewer organisational constraints than public firms. Cowie (1999) also stated that private firms receive a different form of subsidy from public firms without further elaboration. However, Lan and Lin (2003) found that ownership did not affect efficiency based on their worldwide study. No explanation was given for the finding.

For urban rail services, Mizutani (2004) found that there was not much difference in efficiency between private firms and public firms in Japan — when variable costs were measured. He recommended measuring variable costs instead of total costs since rail firms could not optimise their facilities in the short run. He stated three reasons for his finding. First, smaller private firms are regional monopolies, and fare regulation protects them. Second, public firms are relatively new, and new technology saves operating costs. Third, governmental budget constraints that time decreased wasteful operating expenditures. However, from his worldwide study, Canavan (2015) found that private firms were less efficient than public firms. While suggesting that the finding needed further examination, he stated that one possible reason was "private metros may be more likely to sacrifice services in an effort to profit maximise" (Canavan, 2015, p. 104). We assumed he meant service outputs.

Although these studies are similar in efficiency definition, they differ in the sample, period, and efficiency type. It can be why their findings are inconsistent (Perry et al., 1988). Table 2 on page 33 lists such differences.

Table 2. The difference in sample, period, and efficiency type between studies assessing the efficiency of private firms in the land transport sector.

Author(s)	*Sample*	*Period*	*Efficiency Type*
Caves and Christensen (1980)	Canadian Railroads	1956-1975	technical efficiency
Filippini and Maggi (1993)	railway firms in Switzerland	1985-1988	cost efficiency
Cowie (1999)	railway firms in Switzerland	1995	technical efficiency
Pollitt and Smith (2002)	British Rail	1999-2000	cost efficiency
Mizutani and Urakami (2003)	bus firms in Japan	1997-2000	cost efficiency
Lan and Lin (2003)	railway firms worldwide	1999-2001	technical efficiency
Mizutani (2004)	urban rail firms in Japan	1970, 1975, 1980, 1985, 1990, 1995, 2000	cost efficiency
Ottoz et al. (2009)	bus firms in Italy	1998-2002	cost efficiency
Scheffler et al. (2013)	bus firms in Germany	2004-2009	technical efficiency
Canavan (2015)	urban rail firms worldwide	2004-2012	technical efficiency

Because of this, we are motivated to explore the ownership effect on different efficiency types — given the same sample in the same period. There are two efficiency types: cost efficiency and technical efficiency.

The ownership effect on cost efficiency can be measured using a trans-log cost function, while the ownership effect on technical efficiency can be measured using a DEA-Tobit regression.

Besides a trans-log cost function, a DEA-Tobit regression can also measure the ownership effect on cost efficiency. It brings us to another motivation: to explore the ownership effect on cost efficiency — given the same sample in the same period but different methods.

It is also important to highlight that the studies on urban rail firms listed above (i.e., Mizutani (2004) and Canavan (2015)) did not account for the mode effect. Furthermore, we are unaware of any study that accounted for the mode effect when assessing the ownership effect on efficiency in the urban rail sector. For this reason, we are motivated to include the mode effect in the models when exploring the ownership effect on efficiency in the Japanese urban rail sector.

We are also motivated to explore whether private firms in the Japanese urban rail sector have better cost efficiency than other firms. Theoretically, private firms are expected to be more cost-efficient than other firms.

Therefore, in Research Study 2 (Chapter 6), we aim to explore the ownership effect on cost efficiency in the Japanese urban rail sector. In doing so, we will:

a. determine whether adding the ownership variable into Research Study 1's trans-log cost function model does not materially change the coefficients elsewhere,
b. explore whether different methods (i.e., trans-log cost function and DEA-Tobit Regression) would yield similar results, and
c. determine whether private firms are more cost-efficient than other firms.

2.2.4 Service Effectiveness

While there are many studies on cost efficiency (and technical efficiency), there is very little attention on private firms' service effectiveness in the land transport sector, especially on rail services. For example, Lan and Lin (2003) investigated the ownership effect on technical efficiency — but not service effectiveness — when they measured both performance dimensions on railways in America, Africa, Asia, Europe and Oceania.

To our knowledge, only Currie and De Gruyter (2016) investigated the effect of ownership on service effectiveness. They evaluated the performance of light rail services in the USA and Australia and found private firms performed better in service effectiveness than public firms. They explained that competitive tendering and performance-based contracts tied to private firms have resulted in better ridership performance over time than direct awards given to public firms.

Because of this, we are motivated to explore whether private firms in the Japanese urban rail sector have better service effectiveness than other firms. Theoretically, private firms are expected to be more service effective than other firms.

2.2.5 Cost Effectiveness

Like service effectiveness, few empirical studies exist on private firms' cost effectiveness in the land transport sector, especially on rail services. They include authors using the term 'efficiency' in their studies but actually measured cost effectiveness, i.e., the relationship between service inputs and service consumption. One example is Costa et al. (2021).

Note that even though we have expanded our scope of literature from the rail sector to the land transport sector for cost efficiency, service effectiveness and cost effectiveness, we found that the studies on private firms’ service effectiveness and cost effectiveness are not as many as those on private firms’ cost efficiency. However, we decided not to include the air and maritime transport sectors because of their market uniqueness.

There seems to be no conclusive answer to the ownership effect (i.e., private firms’ effect) on cost effectiveness in the land transport sector, except for urban rail services. Regarding bus services, Merkert et al. (2017) found that private firms were less cost-effective than other firms worldwide. They explained that due to several factors, the result contradicted the predictions of economic theories. First, public-owned systems dominated the sample. Second, private and public entities could receive public support through subsidies, transfer payments, or contractual revenue guarantees. Third, high service standards cost more, so bus rapid transit systems might have needed more public assistance.

Regarding railway services, Kunz and Shiel (1988) concluded that private firms' cost effectiveness performance could not be differentiated from other firms in the United Kingdom, France, Germany, Japan, New Zealand, Australia, the United States of America, and Canada. According to them, the fact that the organisational and institutional changes happened so recently could explain why the results were unclear. It could take years to affect a shift in corporate culture and organisational structure, and it might take even longer to see the results of those efforts.

However, in the case of urban rail services, private firms are found to be more cost-effective than other firms. For example, Mizutani (1994) found that private firms were more cost-effective than other firms in Japan. He explained that private firms were superior in many ways. They required fewer subsidies, travelled faster, charged lower fares, experienced higher labour productivity[34], and benefitted from a lesser average employee wage than public firms. Costa et al. (2021) also found that private firms were more cost-effective than other firms in Portugal. Private firms were said to be capable of delivering higher productivity levels and social welfare. Because of this, we are motivated to explore whether private firms in the Japanese urban rail

[34] Due to the practice of contracting-out.

sector have better cost effectiveness than other firms. Theoretically, private firms are expected to be more cost-effective than other firms.

In the literature, many authors treated cost effectiveness as cost efficiency. A recent example is Costa et al. (2021), who used costs as the input and revenue as the output in their DEA-OLS models when measuring the effects of ownership on the efficiency of urban rail firms. Using these terms inaccurately may give a partial picture of the overall performance — especially when there is a difference in how exogenous factors (such as density, scale, and mode) affect cost efficiency and cost effectiveness. For this reason, we are motivated to evaluate how density, scale and mode affect cost efficiency, service effectiveness, and cost effectiveness.

Therefore, in Research Study 3 (Chapter 7), we aim to explore further the ownership effect on each performance dimension (i.e., cost efficiency, service effectiveness and cost effectiveness) in the Japanese urban rail sector and investigate the density, scale, and mode effects on each performance dimension. In doing so, we will:

a. determine whether private firms are more service effective than other firms,
b. determine whether private firms are more cost-effective than other firms,
c. compare and evaluate private firms' performance in cost efficiency, service effectiveness, and cost effectiveness, and
d. compare and evaluate how density, scale, and mode affect cost efficiency, service effectiveness, and cost effectiveness.

In this study, private firms' cost efficiency from Research Study 2 is used to compare and evaluate private firms' service effectiveness and cost effectiveness.

Chapter 3 Methodology

In this chapter, we elaborated on the methods utilised in the research studies based on our research aims. We have three main research aims. First, we aim to understand the cost structure of each urban rail mode in Japan and determine whether there is any significant difference between them. Second, we aim to explore the ownership effect on efficiency[35] in the Japanese urban rail sector. Third, we aim to explore further the ownership effect on each performance dimension (i.e., cost efficiency, service effectiveness and cost effectiveness) in the Japanese urban rail sector and investigate the density, scale, and mode effects on each performance dimension.

Each aim will have a dedicated research study. So, there are three research studies, and they were carried out in stages since there is a methodology linkage between one study and another that follows. The model specified in the first research study was subsequently utilised in the second research study. Furthermore, we referred to some findings from the preceding study when discussing the methods used in the second and third research studies.

3.1 Method for Research Study 1

In Research Study 1 (Chapter 5), we aim to understand the cost structure of each urban rail mode in Japan and determine whether there is any significant difference between them. In doing so, we will:

a. determine whether operating costs vary between modes and whether there is a significant difference between them,
b. determine whether economies of density characteristics vary between modes and whether there is a significant difference between them, and

[35] Cost efficiency and technical efficiency.

c. determine whether economies of scale characteristics vary between modes and whether there is a significant difference between them.

We chose a cost function regression because it can offer valuable insights into the cost structure of each rail mode for a given range of operation size — in terms of both density and scale. The cost function is widely used in urban rail and broader literature. Some examples include Couto and Graham (2008), Mizutani and Uranishi (2013), and Wheat and Smith (2015). In rail services, the size of an operation is typically measured either by the output volume (such as car km) or the network length (such as track km). Output can also be expressed in terms of density (e.g., car-km per track-km) to understand the impact of increasing traffic on a fixed network. Henceforth, RTD measures the benefit (decrease in unit cost) or setback (increase in unit cost) if the density is increased. RTS measures the benefit (reduction in unit cost) or setbacks (increase in unit cost) if the scale is increased (output and network length increase together).

Increasing either density or scale may result in one of these three circumstances:

a. an increasing RTD or RTS in which the marginal costs are lower than the average costs,
b. a constant RTD or RTS in which the marginal costs are the same as the average costs, or
c. a decreasing RTD or RTS in which the marginal costs are higher than the average costs.

Generally, there are two types of cost functions: Cobb-Douglas and trans-log. The Cobb-Douglas is an example of the first-order functional form, while the trans-log is an example of the second-order functional form. They are polynomial cost functions which can accommodate microeconomic theories (Reynès, 2011). Greene (2008, p. 100) stated, "the Cobb-Douglas and trans-log models overwhelmingly dominate the applications literature in stochastic frontier and econometric inefficiency estimation". The Cobb-Douglas cost function has the advantage of being universally smooth and convex isoquants. It is a well-behaved function. However, this function adopts a strong assumption stating that elasticities are constant. Trans-log cost function, alternatively, is less restrictive than Cobb-Douglas — allowing the accommodation of the U-shaped average cost curve.

There are many trans-log cost function studies on rail services, including a mix of regional, long-distance, commuter and some urban operations. Wheat and Smith (2015) estimated a hedonic trans-log cost function on 28 British railway operators concerning mergers between train operators. Couto and Graham (2008) analysed the role of allocative inefficiency on the cost by estimating a trans-log cost function on 27 railway firms from European countries. Mizutani and Uranishi (2013) applied the trans-log cost function on 30 railway organisations in 23 European and East Asian OECD countries to evaluate vertical and horizontal separation cost implications.

Walter (2011) used the trans-log cost function for urban rail services to evaluate cost efficiency and its determinants of multi-output transit operators[36] in Germany. However, he did not split tram, light railway, and metro services "into different outputs because there is no clear definitional separation between these services" Walter (2011, p. 30). Savage (1997) evaluated the costs of 13 heavy rails and nine light rails in the United States by applying the trans-log cost function[37]. The study was conducted over two decades ago, and the current urban rail environment may differ.

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[36] These operators provided bus, tram, light rail, and metro services. However, it cannot be determined whether every firm provided every service. The description of ‘unbalanced data’ suggests that not every firm provided every service. See Walter, M. (2011). Some determinants of cost efficiency in German public transport. *Journal of Transport Economics and Policy (JTEP)*, *45*(1), 1-20.

[37] The author included each type in the same trans-log cost function. Each type was represented by dummy variables. However, when evaluating economies of density and system size, the author divided the 22 systems into six generic groups and plotted average variable cost curve for each group.

The cost function studies on rail services were prevalent in the North American and European regions, according to a survey by Catalano et al. (2019). These studies were uncommon in the Asian region, possibly due to the scarcity of data. Japan, perhaps being a developed nation, is an exception. Mizutani et al. (2009) used the Cobb-Douglas cost function of 34 private railway firms to evaluate the effects of yardstick regulation in Japan. Mizutani and Shoji (2004) compared the infrastructure maintenance costs of a vertically separated railway company against 76 vertically integrated railway firms in Japan using the trans-log cost function. Mizutani (2004) explored the optimal size of a private urban rail company by applying the trans-log cost function to 56 railway firms in Japan.

In estimating a cost function, the trans-log model is typically preferred over the Cobb-Douglas model as the former "offers greater flexibility with respect to the relationship between the cost and the explanatory variables, which may offer more intuitive economic interpretations" (Smith et al., 2017, p. 628). Cobb-Douglas is nested within trans-log. Therefore, testing can be done to evaluate whether additional terms in the trans-log are necessary. Note that other factors are also important in the model selection.

3.1.1 Trans-log Cost Function Model

We specified a trans-log cost function model in which the traffic density variable (car-km/track-km) replaced the output variable (car-km). Principally, using either variable in the model would yield the same RTD and RTS — except that the former allows for a more straightforward calculation of the RTS than the latter as shown in (1) and (2) respectively.

$$RTS_{D_t} = \left[\frac{\partial LnC}{\partial LnN}\right]^{-1} \text{ for } LnC = \alpha + \beta_{D_t} LnD_t + \beta_N LnN \qquad \textbf{(1)}$$

$$RTS_Q = \left[\frac{\partial LnC}{\partial LnQ} + \frac{\partial LnC}{\partial LnN}\right]^{-1} \text{ for } LnC = \alpha + \beta_Q LnQ + \beta_N LnN \qquad \textbf{(2)}$$

Where:

D_t = traffic density; Q = output; C = cost; N = network length; α = constant; β = coefficient value.

We divided the continuous variable by their sample mean. By doing so, we could easily hold variables other than traffic density and network length at their mean values when plotting the RTD and the RTS. It also means that the coefficient on the first-order density and scale terms can be interpreted as elasticities evaluated at the sample mean. All continuous variables were subsequently converted to the natural log form. This practice enabled us to treat the coefficients on the right-hand side of the equation as the cost elasticity.

We introduced mode dummy intercepts as follows so that we can evaluate whether operating costs vary between modes:

$$Ln\left(\frac{C_{ELM}}{\bar{C}_{ELM}}\right) = \alpha + \beta_{DM_{MR}} DM_{MR} + \beta_{DM_{UG}} DM_{UG} \qquad \textbf{(3)}$$

Where:

α = constant

β = coefficient value

C_{ELM} = cost of energy, labour, and material & repairs

DM_{MR} = mode dummy for monorail

DM_{UG} = mode dummy for under-ground

DM_{OG} = mode dummy for over-ground (omitted)

We introduced mode dummy interactions with density and scale as follows so that we can evaluate whether economies of density and economies of scale vary between modes:

$$Ln\left(\frac{C_{ELM}}{\bar{C}_{ELM}}\right) = \alpha + \beta_{D_t} Ln\frac{D_t}{\bar{D}_t} + \beta_{D_t} Ln\frac{D_t}{\bar{D}_t}\beta_{DM_{MR}} DM_{MR} + \beta_{D_t} Ln\frac{D_t}{\bar{D}_t}\beta_{DM_{UG}} DM_{UG} + \beta_N Ln\frac{N}{\bar{N}} + \beta_N Ln\frac{N}{\bar{N}}\beta_{DM_{MR}} DM_{MR} + \beta_N Ln\frac{N}{\bar{N}}\beta_{DM_{UG}} DM_{UG} \qquad \textbf{(4)}$$

Where:

α = constant

β = coefficient value

C_{ELM} = cost of energy, labour, and material & repairs

D_t = traffic density (car-km/track-km)

N = network length (track-km)

DM_{MR} = mode dummy for monorail

DM_{UG} = mode dummy for under-ground

DM_{OG} = mode dummy for over-ground (omitted)

The base model is defined as follows:

$$Ln\left(\frac{C_{ELM}}{\bar{C}_{ELM}}/\frac{P_M}{\bar{P}_M}\right) = \alpha + \beta_{D_t} Ln\ \frac{D_t}{\bar{D}_t} + \beta_{P_E} Ln\left(\frac{P_E}{\bar{P}_E}/\frac{P_M}{\bar{P}_M}\right) + \beta_{P_L} Ln\left(\frac{P_L}{\bar{P}_L}/\frac{P_M}{\bar{P}_M}\right) + \beta_N Ln\frac{N}{\bar{N}} + \frac{1}{2}\beta_{D_tD_t}\left(Ln\ \frac{D_t}{\bar{D}_t}\right)^2 + \frac{1}{2}\beta_{P_EP_E}\left(Ln\left(\frac{P_E}{\bar{P}_E}/\frac{P_M}{\bar{P}_M}\right)\right)^2 + \frac{1}{2}\beta_{P_LP_L}\left(Ln\left(\frac{P_L}{\bar{P}_L}/\frac{P_M}{\bar{P}_M}\right)\right)^2 + \frac{1}{2}\beta_{NN}\left(Ln\frac{N}{\bar{N}}\right)^2 + \beta_{D_tP_E} Ln\ \frac{D_t}{\bar{D}_t} Ln\left(\frac{P_E}{\bar{P}_E}/\frac{P_M}{\bar{P}_M}\right) + \beta_{D_tP_L} Ln\frac{D_t}{\bar{D}_t} Ln\left(\frac{P_L}{\bar{P}_L}/\frac{P_M}{\bar{P}_M}\right) + \beta_{D_tN} Ln\frac{D_t}{\bar{D}_t} Ln\frac{N}{\bar{N}} + \beta_{P_EP_L} Ln\left(\frac{P_E}{\bar{P}_E}/\frac{P_M}{\bar{P}_M}\right) Ln\left(\frac{P_L}{\bar{P}_L}/\frac{P_M}{\bar{P}_M}\right) + \beta_{P_EN} Ln\left(\frac{P_E}{\bar{P}_E}/\frac{P_M}{\bar{P}_M}\right) Ln\frac{N}{\bar{N}} + \beta_{P_LN} Ln\left(\frac{P_L}{\bar{P}_L}/\frac{P_M}{\bar{P}_M}\right) Ln\frac{N}{\bar{N}} + \beta_{DM_{MR}} DM_{MR} + \beta_{DM_{UG}} DM_{UG} + \beta_{D_t} Ln\frac{D_t}{\bar{D}_t} + \beta_{D_t} Ln\frac{D_t}{\bar{D}_t}\beta_{DM_{MR}} DM_{MR} + \beta_{D_t} Ln\frac{D_t}{\bar{D}_t}\beta_{DM_{UG}} DM_{UG} + \beta_N Ln\frac{N}{\bar{N}} + \beta_N Ln\frac{N}{\bar{N}}\beta_{DM_{MR}} DM_{MR} + \beta_N Ln\frac{N}{\bar{N}}\beta_{DM_{UG}} DM_{UG} + T + \varepsilon \quad \textbf{(5)}$$

Where:

α = constant

β = coefficient value

C_{ELM} = cost of energy, labour, and material & repairs

D_t = traffic density (car-km/track-km)

P_E = energy price

P_L = labour price

P_M = material & repair price

N = network length (track-km)

DM_{MR} = mode dummy for monorail

DM_{UG} = mode dummy for under-ground

DM_{OG} = mode dummy for over-ground (omitted)

T = time (year)

ε = error term

The model excludes the capital costs associated with infrastructure and rolling stock due to two primary reasons. Firstly, these costs are substantial and occur infrequently compared to energy, labour, and material expenses, making short-term facility optimization challenging for rail firms (Mizutani, 2004). Secondly, variations exist among operators concerning the timing of these costs and their depreciation treatment, with private firms more likely to underestimate depreciation compared to public firms (Mizutani, 1994). Consequently, incorporating these costs as input or controlled factors may lead to inaccurate cost structures in the model. Furthermore, the model does not account for new infrastructure investments, depreciation, or taxes. However, it does include maintenance and repair costs for track, cable, and rolling stocks.

In Appendix B, we assessed different regression methods like Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE). We also acknowledged the widespread use of Stochastic Frontier Analysis (SFA) across various domains, including its application to measure efficiency in urban rail contexts (Battese & Coelli, 1995). SFA is an expanded form of standard regression. For instance, the B-C version of the SFA model functions as a random-effects model but incorporates an inefficiency component. Likewise, the "true" random-and fixed-effects models are traditional models that have been adjusted (Titus & Pusser, 2011). However, we chose not to incorporate SFA in our analysis for two main reasons.

Firstly, our objective is to evaluate the efficiency performance of private firms as a group, not individual firms. The efficiency of this group can be gauged by examining the ownership coefficient in regular regression analysis. Our approach has also been used by other authors such as Fumitoshi et al. (2015), who compared the costs of vertical separation, integration, and intermediate organisational structures in European and East Asian railways. Journal of Transport Economics and Policy 2015 Vol. 49 Issue 3 took the same approach of incorporating dummies to capture vertical separation effects, using a cost function, not SFA, as the focus was on the impact of structure, not on country efficiency. SFA is more relevant when the concern is the efficiency of individual firms.

Secondly, the implementation of SFA can be more intricate (Greene, 2005). SFA hinges on specific assumptions regarding error term distribution and inefficiency presence (Street, 2003). Changes in model specification, like using logarithmic transformations or including extra explanatory variables, might render SFA unnecessary and result in a normal OLS residual. In such situations, the entire error term is considered noise, complicating the identification of discrepancies in relative efficiency.

3.2 Method for Research Study 2

In Research Study 1 (Chapter 5), we looked at the cost structure of each urban rail mode in Japan to determine whether they vary. We now move from evaluating the cost structure of urban rail modes to assessing the efficiency of private firms. In Research Study 2 (Chapter 6), we aim to explore the ownership effect on cost efficiency in the Japanese urban rail sector. In doing so, we will:

a. determine whether adding the ownership variable into Research Study 1's trans-log cost function model does not materially change the coefficients elsewhere,
b. explore whether different methods (i.e., trans-log cost function and DEA-Tobit Regression) would yield similar results, and
c. determine whether private firms are more cost-efficient than other firms.

We applied two methods in this study. One is the trans-log cost function, and another is the DEA-Tobit regression. DEA-Tobit is a two-stage modelling approach where a Data Envelopment Analysis (DEA) programme is run on input and outputs to compute efficiency in the first stage. This efficiency is then used in the second stage regression to understand the drivers of efficiency (Tobit regression). The trans-log cost function is parametric, while DEA-Tobit regression is semi-parametric[38]. Nevertheless, they are two widely used methods for deriving efficiency. Nash and Smith (2014) discussed the advantages and disadvantages between them.

Note that we are assessing efficiency that considers efficient use of resources, not just purely benchmarking. This assessment requires the presence of a production frontier. Efficiency is measured based on deviation from the production frontier. Because of that, a parametric approach needs a priori specification of a functional form for production technology, while a non-parametric approach establishes the frontier by 'enveloping' the data with piecewise linear functions or hyperplanes (Karlaftis & Tsamboulas, 2012). We imposed a linear homogeneity condition for the trans-log cost function model and checked for monotonicity. For the DEA-Tobit model, the convexity constraint in the standard DEA method relates to the production frontier and allows economic interpretation (Sigaroudi, 2016; Zhu, 2020).

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[38] DEA is non-parametric, and the Tobit regression is fully parametric. The term semi-parametric refers to the combined approach.

It is worth mentioning that the network DEA method is not the same as the standard DEA method. Convexity constraint is absent in the network DEA method since the multiplier and envelopment models are not equivalent (or dual) under the network DEA (Chen et al., 2014; Zhang et al., 2021; Zhu, 2020). Therefore, we cannot measure efficiency using the network DEA[39].

One advantage of the standard DEA is that it does not necessitate the imposition of restrictive behavioural assumptions such as cost minimisation in the econometric cost function, which requires a functional form specification. The standard DEA is constructed in such a way that it satisfies the monotonicity and curvature restrictions (Reinhard et al., 2000). A drawback is its difficulty separating economies of density and scale. Tobit regression can be applied after running the DEA to address this drawback.

One advantage of the trans-log cost function is that it does not require another regression to distinguish density and scale effects. Another is that it accounts for the allocative efficiency (or inefficiency) associated with various input combinations. A drawback is that it needs input prices, and one obstacle is inconsistencies in the treatment of costs like depreciation and interest. Variable costs (excluding capital costs) can be used to mitigate this.

Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) aims to identify the peer group with the lowest input or highest output. An input-oriented model can seek input minimisation, while an output-oriented model can be used to pursue output maximisation. A business or Decision-Making Unit (DMU) can assess its cost (or technical) efficiency and service effectiveness using the peer group as a reference. An illustration of an input-oriented model is shown in Figure 6 on page 48. There are four

[39] The network DEA method is relatively new and still undergoing development. We prefer to utilise the standard DEA method which has been established in the literature.

distinct DMUs, A, B, C, and D. Different input combinations (input one and input 2) are used by the respective DMUs at Points A, B, C, and D to generate the same quantity of output. An inner border, known as the efficient frontier, is formed by points B, C, and D. The efficient frontier is considered technically feasible because technically feasible points formed it. DMU A's peer group consists of DMU B and DMU C. Their performance is used to find point E, which is the efficiency goal for DMU A. The technical efficiency of DMU A is then described as the ratio of 0E to 0A, or:

$$TE_{DMU\,A} = 0E/0A \quad \textbf{(6)}$$

A ratio value of 1 means a DMU is fully efficient.

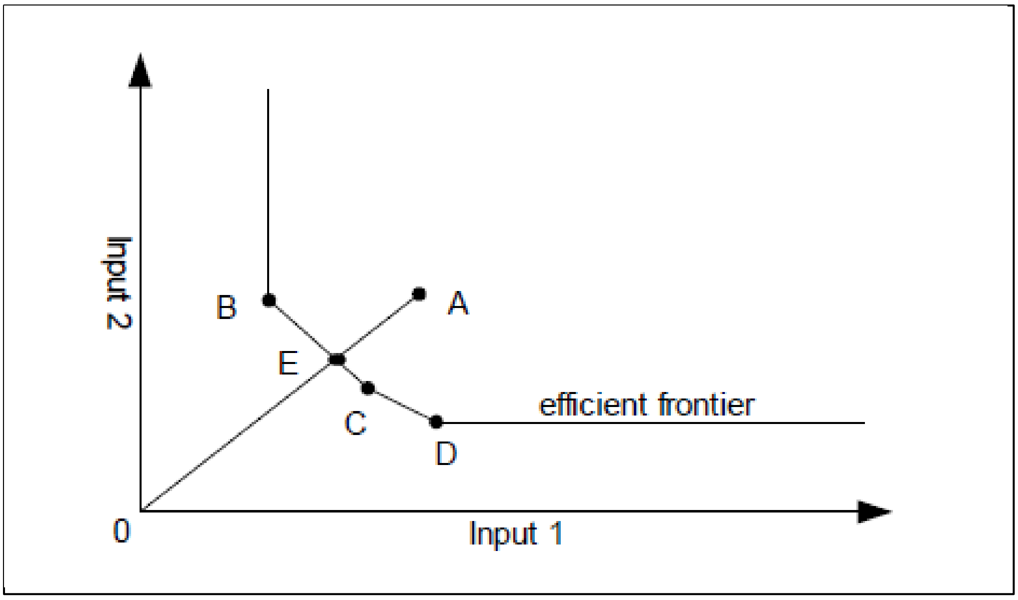

Figure 6. Input-Oriented DEA. Source: Attenborough et al. (2005, p. 56) (with slight modification)

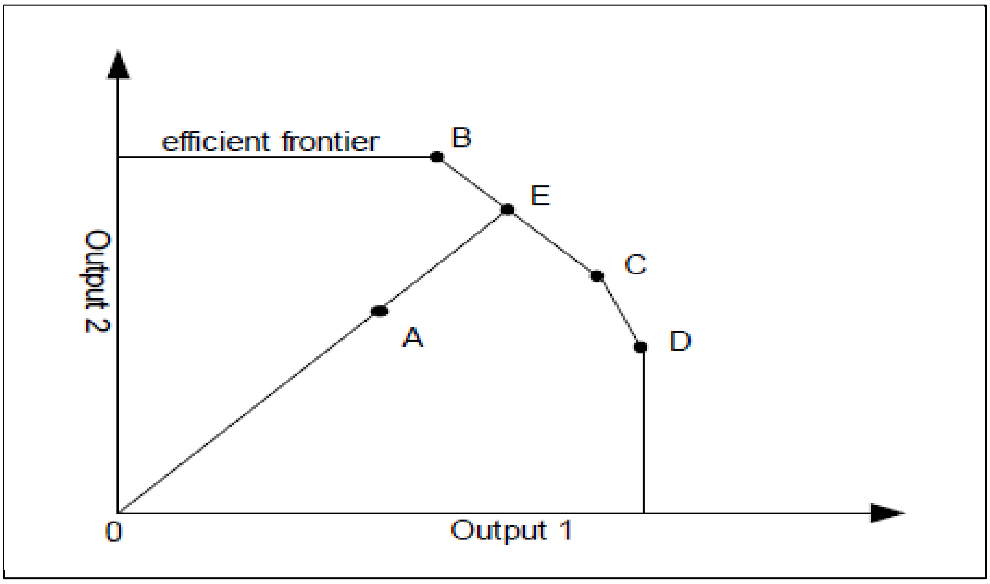

Figure 7. Output-Oriented DEA. Source: Metcalfe (2012) (with slight modification)

Figure 7 on page 49 illustrates an output-oriented model. There are four distinct DMUs, A, B, C, and D. Different combinations of outputs (output one and output 2), produced by the respective DMUs using the same quantity of input, can be seen at Points A, B, C, and D. A line connecting points B, C, and D is known as the efficient frontier. The efficient frontier is considered technically feasible because technically feasible points formed it. DMU A's peer group comprises DMU B and DMU C. Their performance is used to calculate point E, the DMU A efficiency target. The technical efficiency of DMU A is then described as the ratio of 0E to 0A, or:

$$\mathrm{TE}_{\mathrm{DMU\ A}} = 0\mathrm{A}/0\mathrm{E} \qquad \textbf{(7)}$$

A ratio value of 1 means a DMU is fully efficient.

Constant Returns to Scale (CRS), Increasing Returns to Scale (IRS), Decreasing Returns to Scale (DRS) and Variable Returns to Scale (VRS)

Constant Returns to Scale (CRS) indicates that the output increases at the same rate as the input, while Increasing Returns to Scale (IRS) and Decreasing Returns to Scale (DRS) suggest that the output increases at a higher and lower rate, respectively. CRS, IRS, and DRS constitute Variable Returns to Scale (VRS). CRS and VRS are depicted in Figure 8 on page 51 in a "single output - single input" scenario. A, B, C, D, E, and F are each unique DMUs. Points A, B, C, D, E, and F represent the respective DMUs' productivity. DMU C is the most productive of all the units. It has the highest ratio of output to input. A radial line that intersects point C is known as CRS. VRS is the boundary between points A, B, C, D, and E. VRS is split into two sections, with point C in the centre. The section on the left is IRS, while the section on the right is DRS.

VRS considers DMU A, B, C, D, and E efficient. However, according to CRS, only DMU C is considered efficient, whereas DMU A, B, D and E are deemed inefficient. Being on IRS (DMU A and B) and DRS (DMU D and E) made them scale inefficient. DMU F, which does not sit on the frontier, is regarded both technically and scale inefficient. The following equations correspondingly represent how efficient DMU F is on both a technical and scale level:

$$\mathrm{TE}_{\mathrm{DMU\,F}} = \mathrm{XZ}/\mathrm{XF} \tag{8}$$

$$\mathrm{SE}_{\mathrm{DMU\,F}} = \mathrm{XY}/\mathrm{XZ} \tag{9}$$

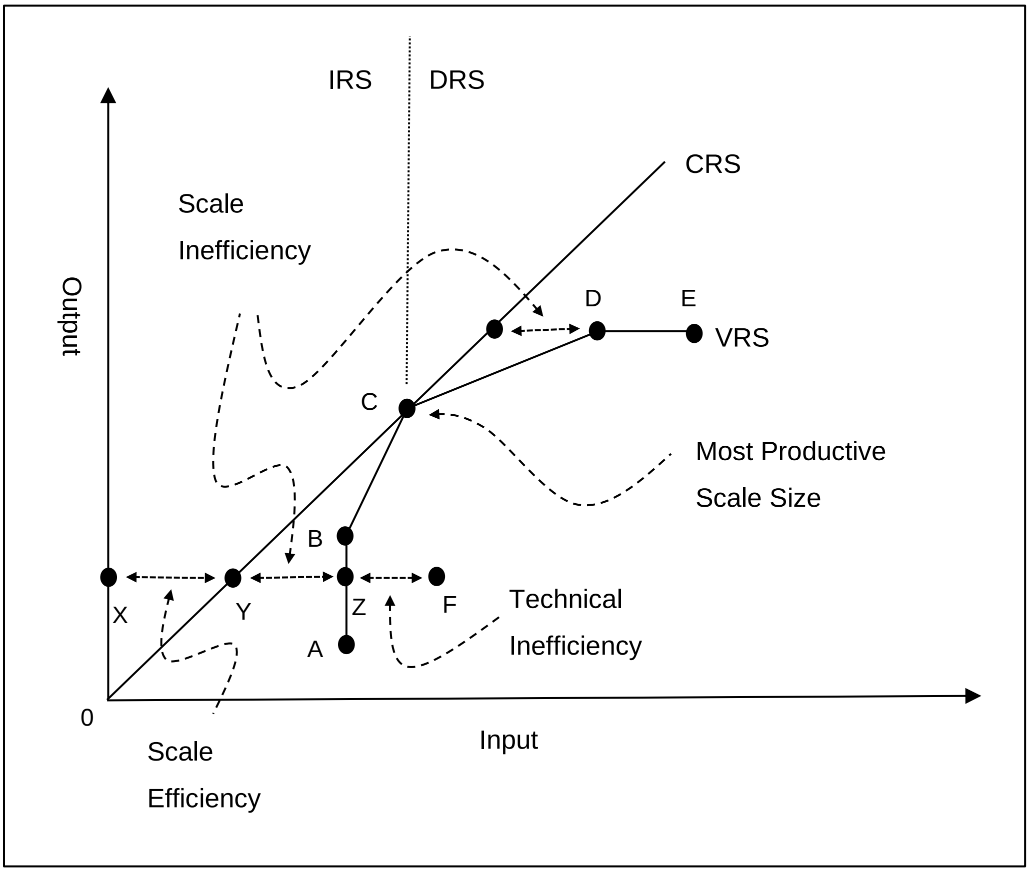

Figure 8. CRS, IRS, DRS and VRS. Source: Cubbin and Tzanidakis (1998, p. 79) (with modification)

Tobit Regression

The Tobit, a censored regression model, is intended to estimate linear relationships between variables when there is left- or right-censoring in the dependent variable — also known as censoring from below and above, respectively (UCLA, 2017). The Tobit model is deemed appropriate to censor the left side of the regression equation between 0 and 1, given that the dependent variable contains an efficiency value between 0 and 1. Studies examining the relationship between efficiency and exogenous factors employ the Tobit model.

DEA-Tobit Regression

Implementing DEA (Data Envelopment Analysis) encounters a challenge due to the presence of a diverse operating environment. Ideally, to yield meaningful outcomes, the operating environment should be uniform. Yang and Pollitt (2009) reviewed various approaches proposed in literature to tackle the issue of dissimilar operating conditions.

Among these approaches are the two-stage models. These models consider the relationship between initial efficiency scores and environmental variables through regression analysis (Holý, 2022). This technique accommodates the impact of environmental factors on efficiency. DEA-Tobit regression stands out as a two-stage model merging Data Envelopment Analysis (DEA) and Tobit regression to handle operating environment variables in efficiency analysis.

DEA, a non-parametric method, gauges the relative efficiency of decision-making units (DMUs) by comparing their input-output connections (Simar & Wilson, 2011b). It produces a score indicating the efficiency of each DMU. Nevertheless, DEA overlooks the influence of external factors on efficiency. To surmount this limitation, DEA-Tobit regression introduces Tobit regression, a parametric method used to analyse censored or constrained dependent variables Blank and Valdmanis (2010). In the DEA context, efficiency scores derived from DEA serve as the dependent variable in the Tobit regression model. This Tobit model permits the incorporation of independent variables representing operating environment factors that impact efficiency[40]. The results of Tobit regression analysis unveil connections between these factors and efficiency scores. The amalgamation of these techniques leads to the term "semi-parametric" for DEA-Tobit regression.

DEA-Tobit regression is particularly advantageous when efficiency scores from DEA are fractional, a common occurrence in efficiency analysis. Fractional regression models like Tobit regression are more suitable for proportions and offer improved specification compared to conventional linear regression models (Martins, 2018).

[40] See Section 3.2.2 for the factors included in our DEA-Tobit regression model.

Oum and Yu (1994) used the two-stage DEA-Tobit regression to obtain residual efficiency for each firm. They considered factors such as density and subsidy that could influence a firm's efficiency. To date, the DEA-Tobit regression continues to be one of the preferred approaches when assessing performance. Three recent examples are Yahia and Essid (2019), Dalei and Joshi (2020), and Dar et al. (2021).

However, there is a debate on whether DEA-Tobit regression is an appropriate approach. Simar and Wilson (1998, p. 49) asserted that "since statistical estimators of the frontier are obtained from finite samples, the corresponding efficiency measures are sensitive to the sampling variations of the obtained frontier". They proposed the application of bootstrapping to define a reasonable data-generating process. Simar and Wilson (2007) further proposed a double bootstrap procedure for better results. Under this new procedure, bootstrapping is done at the first stage DEA and the second stage regression. They also recommended using the OLS regression instead of the Tobit regression at the second stage, as they said the latter was catastrophic in their Monte Carlo experiments.

Since then, some counter-argument surfaced. Tziogkidis (2012a) argued that the equality assumption between the bootstrap and DEA bias used in bootstrapping is implausible. Tziogkidis (2012b) advised that simple bootstrapping should be used instead of double bootstrapping because of the former's consistent and good performance. Double bootstrapping should be avoided due to the technical complexity and sensitivity. Moreover, Tsai et al. (2015, p. 30) explained that the non-bootstrapped scores could still be used as the dependent variable in the second stage Tobit regression since "the significance and magnitude of the impact of the explanatory variables on the efficiency scores are similar, whether the original or bootstrapped TE scores are used".

Foster and Kalenkoski (2013) found that the qualitative results were generally similar between the OLS and Tobit regression. They opined that the OLS regression was not statistically better than the Tobit regression. Their work supported Hoff (2007), who found the OLS regression performed just as well as the Tobit regression at the second stage.

In a more extensive comparison, Banker and Natarajan (2008) found that the DEA-based procedures (i.e. the DEA-Tobit, DEA-OLS, and DEA-ML[41]) performed as well as the parametric methods — when assessing the impact of contextual variables on productivity. Indeed, the former performed better than the latter when evaluating individual productivity. In another extensive comparison, Fitzová and Matulová (2020) concluded that the DEA-Tobit regression, Simar and Wilson's bootstrap approach, and the parametric SFA yield qualitatively similar results.

Despite their variety, these counterarguments do not provide any evidence showing that the DEA-Tobit regression could be used as an alternative to the trans-log cost function regression, which is more complex. Table 3 on page 54 lists the regression techniques and the functional forms that have been proven to have similar results to the DEA-Tobit regression. We are motivated to explore whether there would be similar results between the DEA-Tobit regression and the trans-log cost function if we apply both techniques to Japan's urban rails data.

Table 3. Proven regression techniques and functional forms that have similar results to DEA-Tobit Regression

Author(s)	*Regression Technique(s)*	*Functional Form(s)*	*Measure(s)*
Foster and Kalenkoski (2013)	OLS; Tobit.	Simple Linear	coefficient sign and value
Hoff (2007)	DEA-OLS; DEA-Tobit.	Simple Linear	coefficient sign and value

41 Maximum Likelihood

Author(s)	*Regression Technique(s)*	*Functional Form(s)*	*Measure(s)*
Banker and Natarajan (2008)	DEA-OLS; DEA-MLE; One-Stage Cubic Polynomial MLE; Two-Stage Cubic Polynomial MLE; One-Stage Trans-log OLS; Two-Stage Trans-log COLS; One-Stage Trans-log MLE; Two-Stage Trans-log MLE; Cobb-Douglas.	Log-Linear for DEA-based procedures; Cubic Polynomial; Trans-log Production Function; Cobb-Douglas Production Function	(a) mean absolute deviation percentage, and (b) root mean squared deviation percentage
Fitzová and Matulová (2020)	DEA-Tobit; Single Step Bootstrap DEA (Simar and Wilson 2007); Stochastic Frontier Analysis (SFA).	Log-Linear[42] for DEA-based procedures; Trans-log Production Function	(a) efficiency scores, and (b) coefficient sign and value

We used DEAP 2.1, provided by Coelli (1996), to generate CRS and VRS efficiency scores. DEAP 2.1 generates non-bootstrapped DEA scores. The non-bootstrapped DEA scores are still being used in recent literature, such as by Fitzová et al. (2018), Yahia and Essid (2019), Dalei and Joshi (2020), and Dar et al. (2021).

3.2.1 Trans-log Cost Function Model

We utilised the trans-log cost function model from Research Study 1. Now, we added an ownership variable. This addition served two purposes. First, we wanted to observe whether adding an ownership variable would significantly alter the results in Research Study 1. The

[42] This is not specifically mentioned by the authors. We assume the log-form variables are used in both DEA based regressions as well as the trans-log regression.

observation tests the robustness of our model and the validity of its results. Second, we wanted to compare the results from a trans-log cost function model against those from a DEA-Tobit regression model. The trans-log cost function[43] is parametric, whereas DEA-Tobit regression is semi-parametric. The trans-log cost function is a single-stage modelling technique that interprets the ownership coefficient as an efficiency effect. DEA-Tobit is a two-stage modelling technique. In the first stage, efficiency is calculated by running a Data Envelopment Analysis (DEA) software on inputs and outputs. This efficiency is then used in the second stage regression (Tobit regression) to determine the efficiency drivers.

3.2.2 DEA-Tobit Regression Model

DEA-Tobit regression has two stages. In the first stage, we set the following specifications to produce DEA cost efficiency scores and DEA technical-efficiency scores:

Type of score	*Input for DEA*	*Output for DEA*
Cost efficiency	C_{ELM} (Yen)	Q (thousand car-km)
Technical efficiency	energy (kWh), labour (persons), rolling stock (unit)	Q (thousand car-km)

We applied input orientation DEA since we assumed firms are expected to provide reliable routine services, limiting their service output adjustment. Other authors who have used input orientation include Kerstens (1996) and Tsai et al. (2015).

In the second stage, Tobit regression, we specified the efficiency scores (i.e., cost efficiency in one regression and technical efficiency in another) as the dependent variable. We then selected D_t (car-km/operating-km), N (operating-km), DM_{MR} (dummy for monorail),

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[43] Note that we do not use Stochastic Frontier Analysis (SFA) as the focus is not on individual firm's efficiency but rather private firms. We can get private firms' efficiency from the coefficient on ownership in the cost function.

DM_{UG} (dummy for under-ground), DO_B (dummy for private firms), and T (year) as the independent variables. These are variables available from our data set.

D_t is relevant for considering economies of density, and N is for economies of scale. It is essential to distinguish density and scale effects since rail services "are subject to economies of traffic density" (Nash & Smith, 2014, p. 8). Mizutani (2004) included these variables when studying the ownership effect on rail efficiency. We included DO_B to determine whether private firms are more service-effective or cost-effective than other firms. We included D_t, N, DM_{MR}, *and* DM_{UG} to evaluate how density, scale, and mode affect cost efficiency.

We converted all variables into the natural log form since "the log-linear (or double logarithmic) functional form yields considerably better statistical results than the linear functional form" (Oum & Yu, 1994, p. 132). We set zero as the upper limit for the dependent variable[44]. The Tobit regression model is defined as follows:

$$LnE = \alpha + \beta_{D_t} LnD_t + \beta_N LnN + \beta_{DM_{MR}} DM_{MR} + \beta_{DM_{UG}} DM_{UG} + \beta_{DO_B} DO_B + T + \varepsilon \quad \textbf{(10)}$$

Where:

E = efficiency scores (either cost or technical efficiency)

D_t = traffic density (car-km/operating-km)

N = network length (operating-km)

DM_{MR} = mode dummy for monorail

DM_{UG} = mode dummy for under-ground

DM_{OG} = mode dummy for over-ground (omitted)

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[44] The dependent variable (i.e., efficiency scores) initially have values between 0 to 1. After conversion into the natural log, the values become negative. Note that Ln (1) = 0. Therefore, the log transformation naturally sets the upper limit as zero.

DO_B = ownership dummy for private firms

DO_G = ownership dummy for other firms (omitted)

T = time (year)

α = constant term

ε = error term

3.2.3 Results Comparison

We compared the results from the trans-log cost function model used in Research Study 2 against those from the model used in Research Study 1. Both are parametric models. The difference is that we added the ownership variable into the former to evaluate the ownership effect on efficiency. There could be some correlation between ownership and mode, and we wanted to inspect how adding ownership changes the other coefficients in the model. Thus, in addition to providing new information on the impact of ownership on costs and efficiency, we can study ownership and mode effects together and check the robustness of Research Study 1's findings to the addition of ownership effects.

We also compared the results from the DEA-Tobit regression model against those from the trans-log cost function model used in this study. The former is semi-parametric, while the latter is parametric. The purpose is to evaluate whether there is any difference between the results. DEA-Tobit regression and trans-log cost function are two different approaches. Perry et al. (1988) mentioned that different analytical methods may cause inconsistent results. So, we inspected how density, scale, mode, and ownership affect:

a. cost efficiency under the trans-log cost function model,
b. cost efficiency under the DEA-Tobit regression model, and
c. technical efficiency under the DEA-Tobit regression.

Chapter 7 (Research Study 2) discusses how ownership generally affects efficiency and how private firms perform in cost efficiency in the Japanese urban rail sector.

3.3 Method for Research Study 3

We assessed the efficiency of private firms in Research Study 2 (Chapter 6). Specifically, we determined whether private firms are more cost-efficient than other firms. We now move from assessing the cost efficiency of private firms to evaluating the service effectiveness and cost effectiveness of private firms.

In Research Study 3 (Chapter 7), we aim to explore further the ownership effect on each performance dimension (i.e., cost efficiency, service effectiveness and cost effectiveness) in the Japanese urban rail sector and investigate the density, scale, and mode effects on each performance dimension. In doing so, we will:

a. determine whether private firms are more service effective than other firms,
b. determine whether private firms are more cost-effective than other firms,
c. compare and evaluate private firms' performance in cost efficiency, service effectiveness, and cost effectiveness, and
d. compare and evaluate how density, scale, and mode affect cost efficiency, service effectiveness, and cost effectiveness.

Recall that in the framework for transit performance introduced by Fielding et al. (1985), cost efficiency is the relationship between service input and service output; service effectiveness is the relationship between service output and service consumption; and cost effectiveness is the relationship between service input and service consumption. Fielding et al. (1985) treated the abovementioned relationships as ratio variables. In DEA, we used one component as input and another as output. In deriving cost efficiency, for example, we used the service input component (i.e., the cost of energy, labour, and material and repairs) as input for DEA; and the service output component (i.e., car-km) as output for DEA.

Also, note that network DEA emerged because of the linkage between these relationships. However, we prefer not to apply network DEA in this study for the same reason we mentioned in the method for Research Study 2 section.

In Research Study 2, we applied parametric and semi-parametric models. Their similar results led to the same conclusions (see Chapter 6). This similarity is not unusual, considering the findings from several other authors. Foster and Kalenkoski (2013) found that the qualitative results are generally similar between the OLS and Tobit regression when carrying out a second-stage regression of efficiency scores on explanatory variables. Their finding concurred with Hoff (2007), who found the OLS regression performed just as well as the Tobit regression at the second stage. In a more extensive comparison, Banker and Natarajan (2008) found the DEA-based procedures (i.e. the DEA-Tobit, DEA-OLS, and DEA-ML[45]) performed as well as the parametric methods — when assessing the impact of contextual variables on productivity. In another comparison, Fitzová and Matulová (2020) concluded that the DEA-Tobit regression, Simar and Wilson's bootstrap approach, and the parametric SFA would yield qualitatively similar results. For this reason, we decided to adopt one method in Research Study 3: the DEA-Tobit regression.

3.3.1 Single-Input Single-Output Specification

In Research Study 2 (Chapter 6), we compared the results from the trans-log cost function, DEA-Tobit regression cost efficiency, and DEA-Tobit regression technical efficiency models. We concluded that among the DEA-Tobit regression models, the DEA-Tobit regression cost efficiency (VRS) model produced the most similar results to the trans-log cost function model. We opine that the strong similarity between DEA-Tobit regression cost efficiency (VRS) model and trans-log cost function model was attributed to the single-input single-output specification that existed in both models.

[45] Maximum Likelihood

In the DEA-Tobit regression cost efficiency (VRS) model, service input (*operating costs in Yen*) was treated as the input for DEA and service output (*thousand car-km*) was treated as the output for DEA. In other words, the cost efficiency refers to the relationship between *operating costs in Yen* and *thousand car-km* — a single-input and single-output specification.

In the trans-log cost function model, service input (*operating costs in Yen*) was placed on the left-hand side of equation and service output (*thousand car-km*) was placed on the right-hand side of equation. When other factors are hold constant, the model shows the relationship between *operating costs in Yen* and *thousand car-km* — the same single-input single-output specification applied in the DEA-Tobit regression cost efficiency (VRS) model.

Single-input single-output specification can be found in several cost function studies. Some examples include those of Fumitoshi Mizutani (1997), Mizutani (2004), and Mizutani et al. (2009). This specification can also be found in several DEA studies like those of Banker and Natarajan (2008), Simar and Wilson (2011a), and Tziogkidis (2012b). However, these DEA studies are simulation rather than empirical.

Sigaroudi (2016) argued that evaluating business performance based on a single input and output ratio is an oversimplification that fails to capture the complexity of businesses and their operating environments. Considering multiple inputs and outputs provides a more comprehensive and accurate assessment of a firm's performance. We agree to this reasoning in the case of evaluating technical efficiency. We used multiple-inputs single-output specification for the DEA-Tobit regression technical efficiency models. To recall, the service inputs were energy (*kWh*), labour (*persons*), and rolling stock (*unit*), and the service output was (*thousand car-km*).

When it comes to measuring cost efficiency and cost effectiveness, we opine that treating operating costs as a single input is sufficient since the costs generally reflect all consumed resources. Perhaps there can be additional service output variable(s) — such as *service quality level*

— in addition to the typical service output variable used in the literature (i.e., *car-km*). We admit that one limitation of our research is difficulty in accessing additional data. In the concluding chapter (Chapter 8), we recommend considering *service quality level* if such data is accessible.

For Research Study 3, we used single-input single-output specification in DEA-Tobit regression cost effectiveness (a semi-parametric approach) since based on our findings in Research Study 2, doing so will produce results that are most similar to the trans-log cost function (a parametric approach). For cost effectiveness, service input (*operating costs in Yen*) was treated as the input for DEA and service consumption (*thousand passenger-km*) was treated as the output for DEA. We also used single-input single-output specification in DEA-Tobit regression service effectiveness to maintain consistency. For service effectiveness, service output (*thousand car-km*) was treated as the input for DEA and service consumption (*thousand passenger-km*) was treated as the output for DEA.

3.3.2 DEA-Tobit Regression

We set the following specifications to produce service effectiveness and cost effectiveness scores:

Type of score	*Input for DEA*	*Output for DEA*
Service effectiveness	Q (thousand car-km)	Y (thousand passenger-km)
Cost effectiveness	C_{ELM} (Yen)	Y (thousand passenger-km)

We used VRS scores since the scale is prevalent in the rail industry (Lan & Lin, 2003; Merkert et al., 2017; Tsai et al., 2015).

For service effectiveness scores, we used output orientation since we assume firms are expected to provide reliable routine services, limiting their service output[46] (car-km) adjustment. Service output denotes

[46] Service output (car-km) is used as the input for DEA in calculating service effectiveness.

supply availability to consumers, and in local transport, providing service output is considered a service obligation (Cowie, 1999; Walter, 2011). Lan and Lin (2003) applied output orientation for service effectiveness when evaluating 39 worldwide railway systems.

We applied input orientation for cost effectiveness scores since demand-related factors partly influence service consumption, and firms have more control over service input (Fitzová et al., 2018). Other authors applying input orientation for cost effectiveness include Kleinová (2016) and Costa et al. (2021).

In the second stage, Tobit regression, we specified the effectiveness scores (i.e., service effectiveness in one regression and cost effectiveness in another) as the dependent variable. We then selected D_t (car-km/operating-km), N (operating-km), DM_{MR} (dummy for monorail), DM_{UG} (dummy for under-ground), DO_B (dummy for private), PD (population density), and T (year) as the independent variables.

We included DO_B to determine whether private firms are more service-effective/cost-effective than other firms.

We included D_t, N, DM_{MR}, *and* DM_{UG} to evaluate how density, scale, and mode affect cost efficiency (measured in Research Study 2), service effectiveness, and cost effectiveness. This inclusion will help us understand more about these performance dimensions' differences.

We included PD since population density positively influences service consumption (Ingvardson & Nielsen, 2018; Lobo & Couto, 2016).

For the same reason, we converted all variables into the natural log form as in Research Study 2. The Tobit regression model is defined as follows:

$$LnFX = \alpha + \beta_{D_t} LnD_t + \beta_N LnN + \beta_{DM_{MR}} DM_{MR} + \beta_{DM_{UG}} DM_{UG} + \beta_{DO_B} DO_B + \beta_{PD} PD + T + \varepsilon \quad \textbf{(11)}$$

Where:

FX = effectiveness scores (either service or cost effectiveness)

D_t = traffic density (car-km/operating-km)

N = network length (operating-km)

DM_{MR} = mode dummy for monorail

DM_{UG} = mode dummy for under-ground

DM_{OG} = mode dummy for over-ground (omitted)

DO_B = ownership dummy for private firms

DO_G = ownership dummy for other firms (omitted)

PD = population density

T = time (year)

α = constant term

ε = error term

Chapter 4 Japan Urban Rail Environment and Data

As noted in the introduction, urban rail in Japan forms the basis for the empirical work in this thesis. The urban rail market in Japan is unique. Unlike many others, "Japanese passenger railways are financially healthy and performing well in metropolitan areas" (Mizutani, 2014, p. 4). The market comprises private, public, and quasi-public[47] operators. Most operators own the rail infrastructure. A few operate the rail infrastructure, and another few run the rail services only.

Furthermore, the regulatory environment in Japan is substantially different from anywhere else in the world. We will discuss eight regulatory aspects in Japan. They are the self-sufficiency principle, diversification strategy, subsidies, market entry and exit, licenses, fare, competition, and regulation.

Self-sufficiency principle

The fundamental principle in Japan has always been that urban rail firms must cover operating and infrastructure costs. This self-sufficiency principle also applies to small private firms. The ratio of fare revenue to operating costs — excluding depreciation and debt interest — should be greater than 100% (Shoji, 2005).

Despite this, most private rail firms provide adequate urban transportation services. They are self-sufficient financially, with profitable rail operations. They have farebox ratios that are far above 100%. Even though the market conditions for urban railway systems in Japanese metropolitan areas may be unique regarding passenger volume, the success of Japanese mass transit is more likely due to the private ownership and business diversification of many railway operators (Shoji, 2001).

[47] Shared ownership between public and private.

Diversification strategy

It has long been the practice of Japanese private rail firms to participate in non-rail businesses in addition to rail operations. Throughout their early years, many private firms engaged in various businesses. These include real estate, theme parks, and other modes of transportation – particularly along the rail lines (Song & Shoji, 2016). This diversification strategy has assisted them in establishing the stable ridership required for long-term success. Externalities such as the effect of housing development along rail lines can be captured, but a deliberate cross-subsidisation strategy is not permitted. The Railway Accounting Regulations clearly distinguished between rail lines and non-rail businesses in financial reporting (Mizutani, 2005).

Diversification confers several benefits (Shoji, 2001), including the following:

- Ridership rises as passengers are drawn to other in-house or group companies,
- Group businesses can take advantage of the large number of people who use the train,
- Profitability, made possible by internalising externalities resulting from the development of rail infrastructure, allows the business (and its affiliated companies) to invest in service enhancements more easily, and
- The business can more easily establish a market-oriented outlook due to the experience gained from operating in a non-rail business environment.

Subsidies

Following the self-sufficiency principle, subsidies are only available for specific investment activities, such as constructing new rail lines, reconstructing infrastructure after natural disasters, modernising facilities, and upgrading crossings. It is important to note that subsidies are unavailable for operational activities (Shoji, 2005).

The government of Japan established several specialised subsidy initiatives for circumstances, most notably for projects involving the construction of new lines, which require significant financial investments. However, these subsidy programmes were applied to the lines supplied by public and quasi-public firms but not to more efficient private firms (Shoji, 2005). Private firms may only be eligible for assistance with interest payments on newly constructed or extended lines, which contributes nothing given the historically low levels of market interest rates. Despite being eligible for construction subsidies and concessionary fare reimbursements for senior citizens, many publicly operated subways operate at a loss (Shoji, 2001).

Market Entry and Exit

The market for new entrants was liberalised mainly in the year 2000 (Mizutani, 2005). The requirement for a demand-supply balance was eliminated because it was a deterrent to competition. Two criteria were connected to this requirement in the old Railway Business Law, which was in effect before 2000. One, it is necessary to ascertain adequate demand for railway service. Two, there should not be any imbalance between supply and demand for railway service when a prospective new entrant enters the market.

Licensing was phased out and replaced by a permission system, allowing more market players to be present. Permission is granted if a firm meets the following criteria:

a. it possesses a sound business strategy,

b. it complies with applicable safety regulations,

c. it functions appropriately, and

d. it assumes financial and technological risk.

The permission granted is not time limited. However, permission will be revoked upon negligence or market exit. If a firm's operation is no longer financially viable, it may shut down, but it must notify the Ministry and the relevant local governments one year before ceasing operations. Before the permission system, a firm may cease operations only with the approval of the Ministry when the cessation of service does not jeopardise the public interest.

Licenses

Japanese rail firms are granted three licences under the Rail Business Law (Shoji, 2005). A Class 1 licence is given to a firm that provides rail services through its infrastructure. A Class 2 licence is granted to a firm that operates on borrowed tracks, whereas a Class 3 licence is given to a firm that manages only the infrastructure. A firm classified as Class 1 is vertically integrated, while one classified as Class 2 or Class 3 is vertically segregated. Class 1 licensees are common, but Class 2 and Class 3 licensees are scarce. It is important to note that a rail firm can simultaneously have two different rail classes. For example, a Class 1 licensee can hold a Class 2 license if it uses another firm's track.

Fare

The Ministry regulates passenger fares under the Railway Business Law. All fares must be approved by the Minister of Land, Infrastructure, Transport and Tourism, and the total amount charged should be sufficient to cover a firm's costs and profits. Subsidies are, therefore, unlikely to be sought by firms (Shoji, 2005).

The Ministry of Land, Infrastructure, Transport and Tourism regulates passes and regular tickets by price ceilings. This mechanism allows rail firms to charge any fares within the specified price ceilings. The price ceiling mechanism includes other ticket types, such as serial and group tickets. However, the firms must notify the Ministry of Land, Infrastructure, Transport and Tourism of their fares. The Ministry may order them to change prices if they engage in discriminatory or unfair practices (Mizutani, 2005; Okabe, 2004).

Competition

Competition is minimal, whether for or within the market (Mizutani, 2005). The Railway Business Law requires that when a new railway plan is being considered, the transportation committee appointed by the Ministry of Land, Infrastructure, and Transport solicits input from relevant rail firms and individuals. This condition may act as an indirect barrier to entry. Moreover, the regulator typically permits a firm to operate a monopolistic rail service. It then supervises rail fares and service standards to protect rail users from the dangers of a true monopoly. Therefore, most rail firms are Class 1 licensees that provide rail services on their tracks. Almost all private rail operators in the Tokyo Metropolitan Area who ran trains in 2015 had their rail system and infrastructure (Kato, 2016). Although a few firms operate services on another firm's track, they primarily collaborate to provide more convenient rail services rather than compete. There is competition between lines and firms on some of the most important routes between cities (F. Mizutani, 1997). However, such competition is not widespread. For example, urban rail operations in Tokyo are considered regionally monopolistic (Kato, 2016).

Competition could also cause a setback to social outcomes (Kato, 2016). One example is the competition between the three rail firms, JR East, Keikyu Co., and Tokyu Co., which all run three different lines from Tokyo to Yokohama. Even though this helps improve service and brings down fares, the increased competition among train operators could result in less effective coordination. One explanation is that private businesses do not want to cooperate with rival companies to protect their current clientele from being taken away. Another reason is that private firms do not want to shoulder the investment cost alone to enhance connectivity. In Japan, there is an unspoken guideline that a proposing player is responsible for paying the project's total cost, regardless of whether the project could benefit other stakeholders.

Regulation

A yardstick competition scheme — a form of fare regulation via a benchmarking cost model — has been implemented to avoid the inefficiency associated with monopolistic situations (Mizutani, 2005). There were no public or smaller private railways included in this scheme before a more sophisticated tool was developed in 1997, allowing for the application of the scheme in three distinct groups: 15 large private rail firms, 6 JR passenger firms[48], and ten public rail firms (Okabe, 2004). However, about 130 rail firms still have not been regulated by yardstick competition. The Ministry of Land, Infrastructure and Transport regulates these remaining rail firms separately. The costs of these rail lines are reviewed on a case-by-case basis by the Ministry with confidentiality (Mizutani et al., 2009).

Under this scheme, the regulator establishes several performance measures, such as operating costs, and evaluates the performance of rail operators against these measures. Each rail firm's performance is assessed by comparing its actual costs to the market's standard. For a less efficient rail firm with actual costs that exceed the market's standard costs, the 'reasonable costs' used to determine the fare level are the market's standard costs. Over the evaluation period, the rail firm is expected to maintain costs in line with the market's standard. For a more efficient rail firm with actual costs less than standard market costs, the 'reasonable costs' used to determine the fare level are the average of the firm's actual and market standard costs. Half the difference between actual and market standard costs is returned to the firm to reward its good efforts. The yardstick competition scheme will also evaluate any requests for fare increases.

While the scheme does not foster an ideal environment for competition, it does appear to promote some form of competition. F. Mizutani (1997) found that yardstick competition between large Japanese private rail firms is effective to a certain extent. Firms subjected to yardstick competition significantly improve their cost efficiency compared to firms not subjected to yardstick competition (Mizutani et al., 2009).

[48] JR is the abbreviation of Japan Railways Group. JR has one freight operator (Japan Freight) and six passenger operators (Hokkaido, East Japan, Central Japan, West Japan, Shikoku, and Kyushu). Almost all passenger services are provided within the respective areas.

Further Note on Yardstick Competition

25 of the observed firms are regulated under the Yardstick Competition (see Table 4 on page 72), whereas the remaining 21 firms are separately regulated by the Ministry of Land, Infrastructure and Transport (MLIT) on a case-by-case basis by the Ministry with confidentiality Mizutani et al. (2009).

Fumitoshi Mizutani (1997) discovered that yardstick competition between large Japanese private rail operators is effective to some extent from 1980 to 1993. Mizutani et al. (2009) discovered that firms subjected to yardstick competition considerably improved their cost efficiency compared to firms not subjected to yardstick competition from 1995 to 2000. However, Mizutani and Usami (2016) stated that the statistical significance of yardstick regulation explained by dummy variable was only detected at 10% level, implying that its effect may be minimal. They also examined the performance of firms subject to yardstick competition and those subject to full cost pricing from 1990 to 2011. They did not find any clear evidence that the yardstick regulation for large private railways improved productivity when compared to the traditional full-cost price regulation for small private railways.

We concluded that adding yardstick competition or regulation dummy variable is not necessary since for the most part of our sample period (i.e., 2004-2011 of 2004-2015), there is no significant difference between firms that are regulated under the yardstick competition and firms that are regulated under the full cost pricing.

Table 4. Firms that are subject to Yardstick Competition

ID	*Name*	*Yardstick Competition*	*Metropolitan Area*	*Private*	*Quasi-public*	*Public*	*Over-Ground*	*Monorail*	*Under-Ground*
1	Tobu (Tōbu Railway)	Yes	Tokyo (Kantō)	○			○		
2	Seibu (Seibu Railway)	Yes	Tokyo (Kantō)	○			○		
3	Keisei (Keisei Electric Railway)	Yes	Tokyo (Kantō)	○			○		
4	Keio (Keiō Corporation)	Yes	Tokyo (Kantō)	○			○		
5	Odakyu (Odakyū Electric Railway)	Yes	Tokyo (Kantō)	○			○		
6	Tokyu (Tōkyū Corporation)	Yes	Tokyo (Kantō)	○			○		
7	Keikyu (Keihin Electric Express Railway)	Yes	Tokyo (Kantō)	○			○		

ID	*Name*	*Yardstick Competition*	*Metropolitan Area*	*Private*	*Quasi-public*	*Public*	*Over-Ground*	*Monorail*	*Under-Ground*
8	Soutetsu (Sagami Railway (Sōtetsu))	Yes	Tokyo (Kantō)	○			○		
9	Meitetsu (Nagoya Railroad)	Yes	Nagoya (Chūkyō)	○			○		
10	Kintetsu (Kintetsu Railway)	Yes	Nagoya (Chūkyō)	○			○		
11	Nankai (Nankai Electric Railway)	Yes	Keihanshin	○			○		
12	Keihan (Keihan Electric Railway)	Yes	Keihanshin	○			○		
13	Hankyu (Hankyū Corporation)	Yes	Keihanshin	○			○		
14	Hanshin (Hanshin Electric Railway)	Yes	Keihanshin	○			○		

ID	Name	Yardstick Competition	Metropolitan Area	Private	Quasi-public	Public	Over-Ground	Monorail	Under-Ground
15	Nishitetsu (Nishi-Nippon Railroad)	Yes	Fukuoka–Kitakyushu	○			○		
16	Tokyo Metro (Tokyo Metro)	Yes	Tokyo (Kantō)	○					○
17	Shinkeisei (Shin-Keisei Electric Railway)	No	Tokyo (Kantō)	○			○		
18	Tokyo monorail (Tokyo monorail)	No	Tokyo (Kantō)	○				○	
19	Senboku (Semboku Rapid Railway)	No	Keihanshin	○			○		
20	Kobe (Kōbe Electric Railway)	No	Keihanshin	○			○		
21	Sanyo (Sanyo Electric Railway)	No	Keihanshin	○			○		

ID	*Name*	*Yardstick Competition*	*Metropolitan Area*	*Private*	*Quasi-public*	*Public*	*Over-Ground*	*Monorail*	*Under-Ground*
22	Nose (Nose Electric Railway)	No	Keihanshin	○			○		
23	Hokushin (Hokushin Kyūkō Electric Railway)	No	Keihanshin	○			○		
24	Kita Kyushu (Kitakyushu Monorail)	No	Fukuoka–Kitakyushu			○		○	
25	Saitama new transit (Saitama New Urban Transit)	No	Tokyo (Kantō)		○			○	
26	Saitama Rapid (Saitama Railway)	No	Tokyo (Kantō)		○				○
27	Hokuso (Hokusō Railway)	No	Tokyo (Kantō)		○				○

ID	*Name*	*Yardstick Competition*	*Metropolitan Area*	*Private*	*Quasi-public*	*Public*	*Over-Ground*	*Monorail*	*Under-Ground*
28	Chiba monorail (Chiba Urban Monorail)	No	Tokyo (Kantō)		○			○	
29	Yokohama seaside (Yokohama New Transit)	No	Tokyo (Kantō)		○			○	
30	Yurikamome (Yurikamome)	No	Tokyo (Kantō)		○			○	
31	Tokyo rinkai (Tokyo Waterfront Area Rapid Transit)	No	Tokyo (Kantō)		○				○
32	Toyo rapid (Tōyō Rapid Railway)	No	Tokyo (Kantō)		○				○
33	Tama monorail (Tama Toshi Monorail)	No	Tokyo (Kantō)		○			○	

ID	*Name*	*Yardstick Competition*	*Metropolitan Area*	*Private*	*Quasi-public*	*Public*	*Over-Ground*	*Monorail*	*Under-Ground*
34	Yokohama rapid (Yokohama Minatomirai Railway)	No	Tokyo (Kantō)		○				○
35	Kita Osaka (Kita-Osaka Kyūkō Railway)	No	Keihanshin		○		○		
36	Kobe new transit (Kobe new transit)	No	Keihanshin		○			○	
37	Osaka monorail (Osaka monorail)	No	Keihanshin		○			○	
38	Sapporo (Sapporo City Transportation Bureau)	Yes	Sapporo			○			○
39	Sendai (Sendai Subway)	Yes	Sendai			○			○

ID	*Name*	*Yardstick Competition*	*Metropolitan Area*	*Private*	*Quasi-public*	*Public*	*Over-Ground*	*Monorail*	*Under-Ground*
40	Tokyo subway (Toei Subway)	Yes	Tokyo (Kantō)			○			○
41	Yokohama sub (Yokohama Municipal Subway)	Yes	Tokyo (Kantō)			○			○
42	Nagoya sub (Nagoya Municipal Subway)	Yes	Nagoya (Chūkyō)			○			○
43	Kyoto sub (Kyoto Municipal Subway)	Yes	Keihanshin			○			○
44	Osaka sub (Osaka Metro)	Yes	Keihanshin			○			○
45	Kobe sub (Kobe Municipal Subway)	Yes	Keihanshin			○			○
46	Fukuoka (Fukuoka City Subway)	Yes	Fukuoka–Kitakyushu			○			○

4.1 Data and Variables

We used data from 46 Japanese urban rail firms from 2004 to 2015. These firms are located in six major metropolitan areas in Japan, namely Sapporo, Sendai, Tokyo, Nagoya, Osaka (or Keihanshin), and Fukuoka (see Figure 19 on page 191 and Table 37 on page 192 for further details). The data was sourced from Japan's Annual Statistics of Railways and the Statistics of Japan (Japanese Government Statistics). Table 5 on page 80 and Table 6 on page 83 are the variable definitions and descriptive statistics. A table containing complete values of the key variables will consume about 20 pages. Alternatively, a one-page snapshot of the table is provided to give the reader a general idea on the values of the key variables. For this purpose, Table 7 on page 84 shows a snapshot of representative values of key variables.

Operating costs are the sum of the annual *energy*, *labour*, and *material & repair* costs. The capital costs relating to the infrastructure and the rolling stock are excluded from the model for two reasons. Firstly, these costs are high and infrequent compared to energy, labour, and material & repair costs. Rail firms could not optimise their facilities in the short run (Mizutani, 2004). Secondly, operators have variations regarding when these costs are incurred and how their deprecation is treated. Depreciation is more likely to be underestimated in private firms than in public firms (Mizutani, 1994). Therefore, including these costs as input or controlled factors may cause the model to present inaccurate cost structures. Also, new infrastructure investment is not included — so are depreciation and taxes. However, the maintenance and repair costs for track, cable and rolling stocks are included in the model.

Table 5. Variable Definition

Variable	*Definition*	*Unit*	*Research Study 1*	*Research Study 2*	*Research Study 3*
C_{ELM} *(Operating Cost)*	The sum of energy, labour, and material & repairs costs after accounting for inflation*	Yen	✓	✓	✓
P_E *(Energy Price)*	Price per kWh of energy consumed for the specific year after accounting inflation*	Yen	✓	✓	
P_L *(Labour Price)*	Salary per full-time equivalent employee for the specific year after accounting inflation*	Yen	✓	✓	
P_M *(Material Price)*	Material and repair expenditure per rolling stock for the specific year after accounting inflation*	Yen	✓	✓	
Q *(Output)*	The total journey travelled by all rolling stocks for the specific year	Car-km (thousand)	✓	✓	✓
N	Length of track in operation for the specific year	Operating-km	✓	✓	✓

Variable	*Definition*	*Unit*	*Research Study 1*	*Research Study 2*	*Research Study 3*
(Network Length)					
D_t *(Traffic Density)*	The journey travelled by all rolling stocks is divided by the length of the track in operation for the specific year.	Car-km (thousand) per Operating-km	✓	✓	✓
DM_{OG} *(Over-Ground)*	Dummy variable for rail mode: over-ground (Omitted condition)	Binary	✓	✓	✓
DM_{MR} *(Monorail)*	Dummy variable for rail mode: monorail	Binary	✓	✓	✓
DM_{UG} *(Under-Ground)*	Dummy variable for rail mode: under-ground	Binary	✓	✓	✓
DO_B *(Private Firms)*	Dummy variable for ownership: private firms	Binary		✓	✓

Variable	*Definition*	*Unit*	*Research Study 1*	*Research Study 2*	*Research Study 3*
DO_G *(Other Firms)*	Dummy variable for ownership: quasi-public and public firms (Omitted condition)	Binary		✓	✓
T *(Time)*	Time	Year	✓	✓	✓
D_p *(Population Density)*	Population density by serviced prefecture	Person per $1km^2$			✓

* Inflation base year was set at 2015.

Table 6. Summary Statistics for Continuous Variables

Variable	*Observation*	*Firms*	*Time*	*Mean*	*Std. Dev.*	*Min*	*Max*
$CELM$	552	46	12	29,000 Mil.	36,900 Mil.	1,270 Mil.	202,000 Mil.
PE	552	46	12	14.66	3.99	5.70	30.63
PL	552	46	12	8,678,468	1,908,650	2,714,543	21,400,000
PM	552	46	12	24,800,000	11,800,000	7,026,819	87,100,000
Q	552	46	12	72,610.26	89,953.25	2,327.00	425,417.00
N	552	46	12	84.76	116.09	4.10	584.10
D_t	552	46	12	32,202.57	25002.71	4059.54	106,371.30
D_p	552	46	12	4,301.645	3,146.9	69	9,946

Table 7. A Snapshot of the Values of Key Variables

ID	*CELM*	*PE*	*PL*	*PM*	*Q*	*N*	*Dt*	*DMOG*	*DMMR*	*DMUG*	*DOB*	*DOG*	*T*	*DP*
1	98091179197	14.0223	9313059	19979583	297551	463.30	642.24	1	0	0	1	0	2004	1874
2	58771628218	12.2267	10945419	14839288	173130	176.60	980.35	1	0	0	1	0	2004	3782
3	34251184346	12.9305	10384908	22332019	92134	102.40	899.75	1	0	0	1	0	2004	3440
4	48069726056	15.6679	13326554	21223510	114046	84.70	1346.47	1	0	0	1	0	2004	4665
5	62297659114	12.3641	11449859	19217140	158354	120.50	1314.14	1	0	0	1	0	2004	4665
6	76891453141	13.1326	11064293	37823016	161378	100.10	1612.17	1	0	0	1	0	2004	4665
7	43097136972	12.3907	11271853	25696169	112632	87.00	1294.62	1	0	0	1	0	2004	4665
8	17517447992	12.7889	10073882	11672927	47284	35.90	1317.10	1	0	0	1	0	2004	3623
9	55966578785	12.5358	7664465	17153956	193627	480.80	402.72	1	0	0	1	0	2004	798

Note: Refer to Table 5 on page 80 for variable definitions and the measurement used. *ID* number represents a specific firm. Refer to Table 37 on page 192 for more information on *ID* number and the firm it represents.

Energy is electricity utilised for running trains on the track, including relocation[1]. *Energy price* is energy expenditure (Yen) divided by energy consumed (kWh) for the specific year. *Labour* is full-time equivalent permanent and temporary employees, including those who work onboard, at the stations, and on any other premise relevant to the operation and general affairs. *Labour price* is the sum of all salaries (Yen) divided by the number of labour (persons) for the specific year. *Material and repair* are goods and services purchased to maintain trains, tracks, cables, and other operations and advertisement assets. *Material & repair price* is material and repair expenditure divided by the number of rolling stocks for the specific year.

There is no perfect denominator for cost categories covering multiple factors, like trains and tracks. Without further details (i.e., specific expenditure on each factor), we choose the number of rolling stocks as the denominator for *Material & repair price*. The number of rolling stocks is a good proxy because (a) it is relevant for rolling stock maintenance, and (b) it is relevant for variable track maintenance driven by usage. We also find that number of rolling stocks is highly correlated with network length. Numerous papers use the number of rolling stocks as a denominator for material price. One example is Wheat and Smith (2015).

Output is the summation of the journey travelled (km) by each rolling stock for the year. Network length is the track (km) used for providing train services in a particular year.

There are three mode dummies: over-ground[2], monorail, and under-ground. Over-ground consists of those with the most over-ground routes — although part of their route is under-ground. Under-ground consists of those with most routes under-ground — although part of

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[1] such as moving the cars (trains) to the garage, etc.
[2] mode dummy for the over-ground is omitted to avoid dummy variable trap

their route is over-ground. Monorail consists of monorail and Automated Guideway Transit (AGT) operators.

There are two ownership dummies: private[3] firms and other firms. Japan's Annual Report on Railway Statistics defines private, quasi-public and public firms. We combined quasi-public firms with public firms under one category and named them as other firms. The reason is that quasi-public is typically operated by a private operator and financed by the government to preserve the services of mostly unprofitable lines (Saito, 2015; Shoji, 2001). Moreover, our motivation in Research Studies 2 and 3 is to evaluate the cost efficiency, service effectiveness and cost effectiveness of private firms relative to other firms. A dummy value of zero is set when an urban rail is public or quasi-public. A dummy value of unity is set when an urban rail is private. This dummy value assignment is similar to Kerstens (1996).

For ownership, we further investigated two firms:

- Tokyo Metro – Tokyo Metro Co., Ltd is a "special company" established by an Act. The company is considered to have a significant influence on public interest but desirable to be operated as a corporation rather than a public body. The company operates like a private firm since it will likely be privatised later. Tokyo Metro is a private firm in Japan's Annual Report on Railway Statistics. In our research study, we treated Tokyo Metro as a private firm.
- Kita-Kyushu – Kita-Kyushu is not a "special company" like Tokyo Metro, even though Kitakyushu-shi owns all stocks. Kitakyushu is categorised as a private firm in Japan's Annual Report on Railway Statistics. Our research study treated Kita-Kyushu as part of other firms (i.e., quasi-public and public).

Population density is the number of persons per 1km^2 in the prefecture(s) where a firm is serving (i.e., serviced prefecture). For

[3] Ownership dummy for private is omitted to address dummy variable trap.

example, the population density for Tōbu Railway will be those of Tokyo, Saitama, Chiba, Gunma, and Tochigi (see Table 37 on page 192). We note that in some cases, a firm serves only certain parts of a prefecture. However, this is the best available data on population density that we can obtain.

4.2 Correlation between Mode and Ownership

Both mode and ownership dummies are included in Research Studies 2 and 3 to explore whether there will be a significant performance[4] difference between private firms and other firms in Japan's urban rail services if we account for mode differences. Briefly, private ownership tends to be concentrated in the over-ground operation, quasi-public in the monorail and the under-ground operation, and public ownership in the under-ground operation. These are shown in the following table:

Table 8. Mode and Ownership Tabulation

Key
frequency *column percentage*

	OWN			
MODE	1	2	3	Total
1	20 90.91	2 14.29	0 0.00	22 47.83
2	1 4.55	7 50.00	1 10.00	9 19.57
3	1 4.55	5 35.71	9 90.00	15 32.61
Total	22 100.00	14 100.00	10 100.00	46 100.00

Note: For mode, 1 = Over-Ground, 2 = Monorail, 3 = Under-Ground; and for ownership, 1 = Private, 2 = Quasi-Public, 3 = Public.

[4] Cost efficiency, service effectiveness and cost effectiveness.

Pearson Chi2 and Fisher's Exact tests indicated that Mode and Ownership are not independent. These are shown in the following table:

Table 9. Mode and Ownership: Pearson Chi2 dan Fisher's Exact Tests

MODE	OWN 1	2	3	Total
1	240	24	0	264
2	12	84	12	108
3	12	60	108	180
Total	264	168	120	552

```
Pearson chi2(4) = 500.4221   Pr = 0.000
 Fisher's exact =                 0.000
```

Note: For mode, 1 = Over-Ground, 2 = Monorail, 3 = Under-Ground; and for ownership, 1 = Private, 2 = Quasi-Public, 3 = Public.

If quasi-public firms are combined with public firms, the correlation between ownership and mode dummies will be found as in Table 10 on page 88. In addition to the high correlation value between private firms and the over-ground mode, there is also a high correlation value between other firms (quasi-public and public firms) and the over-ground mode. The values are the same, 0.8295, except that the latter is negative.

Table 10. Correlation between the ownership and rail mode dummies (after quasi-public firms are combined with public firms)

Mode	*Private Firms*	*Significance*	*Other Firms*	*Significance*
Over-Ground	0.8295	0.000	-0.8295	0.000
Monorail	-0.2957	0.000	0.2957	0.000
Under-Ground	-0.6337	0.000	0.6337	0.000

Wooldridge (2013, p. 97) stated, "Regardless of how much correlation there is between x_2 and x_3. If β_1 is the parameter of interest, we do not really care about the amount of correlation between x_2 and x_3." Therefore, if the main interest of the regression is to derive cost efficiency while accounting for the possible influential factor(s), the high correlation between the two variables is negligible. However, in Research Studies 2 and 3, we examined private firms' cost efficiency, service effectiveness, and cost effectiveness relative to other firms. When we discounted time (year) in the observation, the number of firms in each mode category is shown in the following table:

Table 11. Number of Firms in Each Mode Category

	OWN		
MODE	1	2	Total
1	20	2	22
2	1	8	9
3	1	14	15
Total	22	24	46

Note: For mode, 1 = Over-Ground, 2 = Monorail, 3 = Under-Ground; and for ownership, 1 = Private firms, 2 = Other firms.

Private firms operate most over-ground services, while other firms operate most monorail and under-ground services. This situation was similarly observed by Mizutani (1994) when comparing the efficiency and costs of private and public urban railways in Japan. However, he mentioned that, in theory, "this should not cause bias in the coefficients" (Mizutani, 1994, p. 168).

Chapter 5 Research Study 1: Understanding the Cost Structure of Urban Rail Modes

5.1 Introduction

In Chapter 2: Review of the Performance of Urban Rail Modes, we explained that stating and recognising mode differences has not been a standard practice. Not all authors considered mode differences in their studies. We also mentioned the benefits of knowing the cost structure[1] of urban rail services when the mode difference is accounted for. There are three key benefits. First, by accounting the operating costs aspect of Cost Benefit Analysis (CBA), policymakers can make a better decision on which mode to construct when considering for a new urban rail project. Second, policymakers can specify an expected output[2] level from an urban rail operator. Third, policymakers can execute a realistic network expansion project for urban rail service. If the CES varies between urban rail modes, the effect of increased traffic and network length on cost will also vary across urban rail modes. In this research study (Chapter 5), we are motivated to understand the cost structure of each urban rail mode[3] in Japan and determine whether there is any significant difference between them.

In Chapter 3: Methodology, we explained that a cost function regression was chosen because it can offer valuable insights into the cost structure of each rail mode for a given range of operation size — in terms of density and scale. Increasing either density or scale may result in one of these three circumstances:

a. an increasing RTD or RTS in which the marginal cost is lower than the average cost,

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[1] Consists of operating costs, cost elasticity w.r.t density, and cost elasticity w.r.t scale
[2] In this context, we specify output as car-km.
[3] Over-ground, monorail, and under-ground.

b. a constant RTD or RTS in which the marginal cost is the same as the average cost, or
c. a decreasing RTD or RTS in which the marginal cost is higher than the average cost.

We further chose the trans-log cost function over the Cobb-Douglas cost function because it is less restrictive – allowing the adoption of the U-shaped average cost curve. The trans-log cost function allows for more nuanced economic interpretations of the cost structure via dynamic cost elasticity. However, the trans-log is not necessarily simple to apply due to the many parameters that must be estimated. It requires selecting an appropriate functional form (Nash & Smith, 2014). This process finds a good functional form for the model, chooses the variables, and adapts economic theories.

We elaborated on this process in Appendix B: Specification of a Functional Form. In brief, we started with a Cobb-Douglas base cost function. Then, we imposed homogeneity of degree one in prices. After that, we added trans-log terms into the equation. We conducted the F-test to see whether adding these trans-log terms would produce a statistically better model. We proceeded with trans-log model expansion when we found that the trans-log model was better. We did so by gradually adding mode dummy intercepts and interactions into the equation. We checked the F-test, AIC, and BIC results. We also checked how cost elasticity behaves w.r.t density and scale. These checks allowed us to identify a sensible model. We added time trend to the model and used different estimators: Ordinary Least Squares, Fixed Effects, and Random Effects. When we compared the results, we found a lot of similarities between estimators. This finding gave us confidence in the strength of our model. We then decided to use the results from Model 6 RE +Time (after purging), which utilised random effects, an estimator. The regression results from Model 6 RE +Time (after purging) can be found in Table 15 on page 112.

5.2 Research Aims and Objectives

In this chapter, we aim to understand the cost structure of each urban rail mode in Japan and determine whether there is any significant difference between them. In doing so, we set the following objectives:

a. to determine whether operating costs vary between modes and whether there is a significant difference between them,
b. to determine whether economies of density characteristics vary between modes and whether there is a significant difference between them, and
c. to determine whether economies of scale characteristics vary between modes and whether there is a significant difference between them.

5.3 Results and Discussion

This section first synthesises the results from simple ratios, which are non-econometric methods. After that, it will discuss the operating costs, RTD, and RTS based on Model 6 RE +Time (after purging) from the trans-log cost function, which is an econometric method. Then, it will discuss the differences between the results from simple ratios and the trans-log cost function.

5.3.1 Simple Ratios

We looked at two types of ratio statistics. One was the average cost per output (Yen per car-km), and another was the average cost per network length (Yen per operating km). Figure 9 on page 93 shows the rail mode average cost[4] per output. There were observable differences between rail modes. Being one mode could increase or decrease the average cost per output compared to another mode. The underground had the highest average cost per output, amounting to

[4] Rail mode average cost was obtained by summing up the yearly average individual cost and dividing it by the number of members within the rail mode.

¥504,467 (£2,728.16[5]), followed by the monorail at ¥406,404 (£2,197.83) and the over-ground at ¥355,413 (£1,922.07).

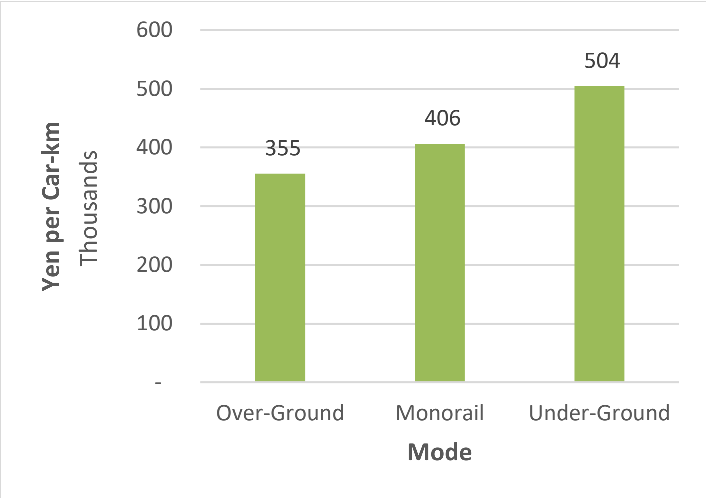

Figure 9. Rail Mode Average Cost per Output

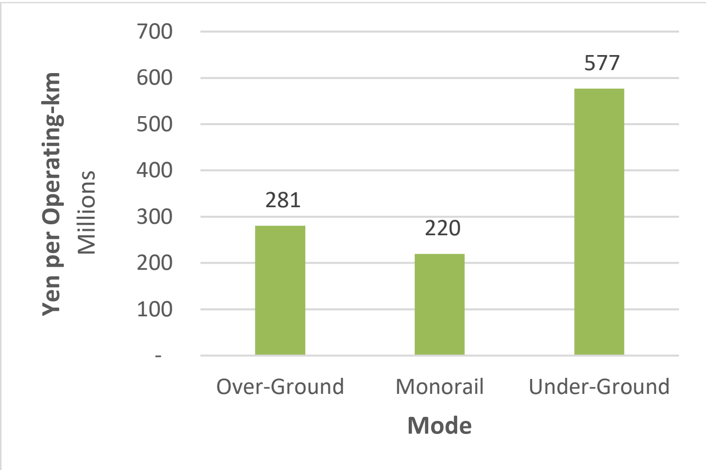

Figure 10. Rail Mode Average Cost per Network Length

The scenario was different when we looked at the average cost per network length. Figure 10 on page 93 shows the rail mode average cost per network length. Although there were still observable differences between rail modes, the order — in the context of which cost more — had changed. The under-ground remained the costliest to operate, with the average cost per network length amounting to ¥577,017,568 (£3,120,511.01). This time, the over-ground had taken

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[5] Converted using the average exchange rate for 2015, at 0.005408.

second place at ¥280,503,910 (£1,516,965.15). The monorail became the least costly at ¥219,663,386 (£1,187,939.59).

Based on the average cost per network length, the gap between the under-ground and any of the other two rail modes was substantial (i.e., more than 100 per cent). However, based on the average cost per output, the gap between the under-ground and any other two rail modes was not relatively substantial (i.e., much less than 100 per cent) — see Figure 9 on page 93.

As the average cost switched from *per output* to *per network length basis*, the over-ground switched from having the lowest average cost to having the second lowest. In turn, the monorail changed from having the second lowest average cost to having the lowest average cost. A question arises regarding which one has the lowest average cost — whether over-ground or the monorail. These different results could result in different rankings depending on cost per output or cost per network length — which invites a statistical model to get a clearer picture.

5.3.2 Relative Operating Costs

To get statistical validity to the findings, we gauged the differences in the operating costs between the rail modes. The over-ground was set as the reference mode. Therefore, differences will be measured based on the percentage deviation from the over-ground operating costs. We calculated *the operating costs relative to the over-ground (CDMO) cost* for the monorail and the under-ground as follows.

$$CDMO_{D_{MM}} = Exponential[\beta_{D_{MM}} + \beta_{D_tD_{MM}} * D_{tD_{MM}} + \beta_{ND_{MM}} * N_{D_{MM}}] \quad (12)$$

$$CDMO_{D_{MU}} = Exponential[\beta_{D_{MU}} + \beta_{D_tD_{MU}} * D_{tD_{MU}} + \beta_{ND_{MU}} * N_{D_{MU}}] \quad (13)$$

Where β is the respective coefficient value, D_t is density (car-km per track-km), N is network length (track-km), D_{MM} is mode dummy for the monorail, and D_{MU} is the mode dummy for the under-ground. Table 12 on page 95 is an excerpt of the regression results from Model 6 RE +Time (after purging). The excerpt shows the coefficients involved in calculating the differences. The complete regression results can be found on page 112.

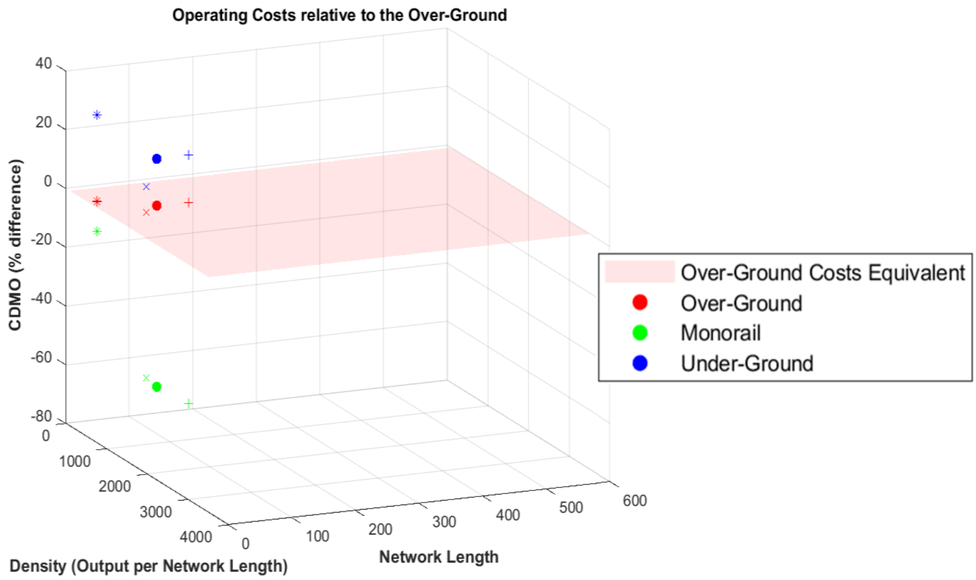
Table 12. The coefficients involved in calculating differences in the operating costs between the rail modes.

Variable Names	*Definition*	*Coefficient*
$LnmcQpN\_DMM$ or $\boldsymbol{\beta}_{D_tD_{MM}}$	Monorail's cost elasticity w.r.t traffic density compared to that of over-ground.	-0.2523734
$LnmcQpN\_DMU$ or $\boldsymbol{\beta}_{D_tD_{MU}}$	Under-ground's cost elasticity w.r.t traffic density compared to that of over-ground.	-0.290507
$LnmcN\_DMM$ or $\boldsymbol{\beta}_{ND_{MM}}$	Monorail's CES compared to that of over-ground.	-0.4184442
$LnmcN\_DMU$ or $\boldsymbol{\beta}_{ND_{MU}}$	Under-ground's CES compared to that of over-ground.	0.0251065
DMM or $\boldsymbol{\beta}_{D_{MM}}$	Monorail's cost elasticity compared to that of over-ground.	- 0.9584722
DMU or $\boldsymbol{\beta}_{D_{MU}}$	Under-ground's cost elasticity compared to that of over-ground.	0.1475098

We calculated *the operating costs relative to the over-ground cost (CDMO)* for the monorail and the under-ground. The density and the network length were set at several mean values (i.e., the sample mean, the over-ground mean, the monorail mean, and the under-ground mean). Setting these mean values allowed us to evaluate the cost differences from the perspective of the market, as well as from the perspective of each rail mode. Figure 11 on page 96 shows the CDMO for the monorail and the under-ground at various means. From every perspective, we found that the monorail's cost was lower than the over-ground. On average, the former's cost was 49.23% lower than the latter.

In comparison, the under-ground's operating costs were higher than the over-ground's. On average, the former's costs were 16.55% higher than the latter. We concluded that, in principle, the monorail has the lowest operating costs, followed by the over-ground and the under-ground.

Although this is similar to the ranking generated by the average cost per network length ratio (see Figure 10 on page 93), the cost gaps between rail modes were not the same. For example, based on the average cost per network length ratio, the cost gap between the under-ground and the over-ground was more than 100 per cent. On the other hand, based on the trans-log cost function, the average cost gap between the two modes was only 17.55%.



Marker	Base Reference	Density Mean	Network Mean	Over-Ground	Monorail	Under-Ground
o	Sample	918.77	84.76	0	-61.65	15.89
+	Over-Ground	945.76	132.82	0	-68.45	16.23
*	Monorail	542.93	15.31	0	-10.38	29.35
x	Under-Ground	1104.69	55.96	0	-56.45	8.71
	Average			0	**-49.23**	**17.55**

Figure 11. The operating costs relative to the cost of the over-ground (CDMO); holding density and network length at various means.

From our point of view, the results from the trans-log cost function, which is Model 6 RE +Time (after purging), should supersede the results from the simple ratios since the former, an econometric model, was much more robust — it had embedded microeconomic principles and account other factors constant. Unlike simple ratios, it also gives statistical validity and allows network length and traffic to be in the model together. This point might be trivial to the policymakers and regulators from the developed regions as the cost function studies on rail services were prevalent in the North American and European regions — see Catalano et al. (2019). However, this point might motivate those from other regions to actively carry out cost function studies on rail services – that is, further their analysis of simple ratios by developing an econometric cost function study[6].

5.3.3 Relative Operating Costs w.r.t Density

We now elaborate on the three-dimensional results in the preceding section (see Figure 11 on page 96) and understand them in more depth — starting by looking at how the relative operating costs of different modes vary with density. To rephrase it, we analyse how density affects the relative operating costs. To make it easier, we turned the three-dimensional results into two-dimensional results. Network length was set at several mean values. We are now able to observe the relative[7] cost behaviour w.r.t density at four network lengths: namely, the average market network length, the average over-ground network length, the average monorail network length, and the average under-ground network length.

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[6] The cooperation from the regulatory body and the operators is essential for data identification and collection for a cost function study.

[7] Bear in mind that the over-ground is the reference mode.

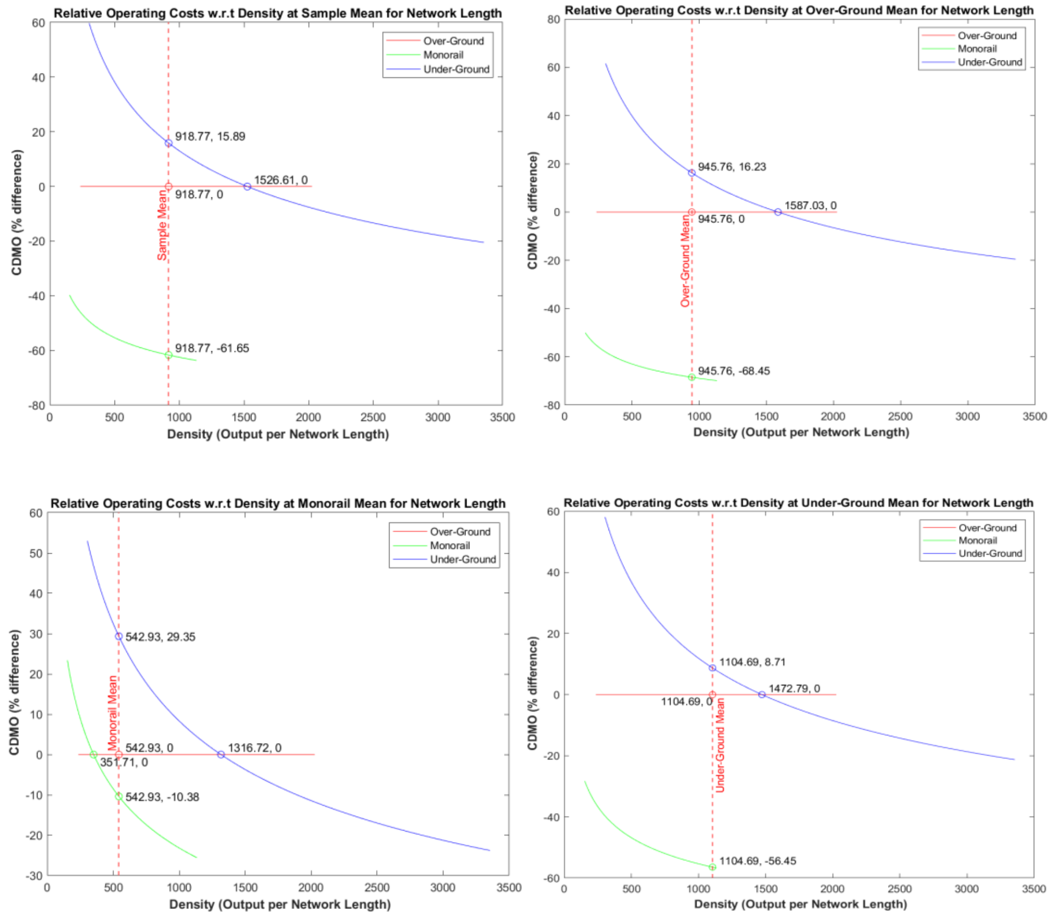


Figure 12. The relative operating costs w.r.t density; holding network length at various means.

Figure 12 on page 98 shows the relative operating costs w.r.t density for the monorail and the under-ground at various network length means (sample, over-ground, monorail, and under-ground means). There are four graphs altogether. They all show similar patterns regarding the relative operating costs for monorail and under-ground. At every network length mean, the relative operating costs for both monorail and under-ground will decrease as their density increases following an output increment. However, the monorail will always experience a lower cost than both over-ground and under-ground. At its average network length (542.93 track-km), the smallest of the four network lengths, the monorail will initially experience higher cost than the over-ground before reaching a density of 351.71 car-km per track-km. On the other hand, under-ground will always experience higher cost than the over-ground before reaching the respective density points — ranging from 1,316.72 to 1,587.03 car-km per track-km — at every network length mean.

5.3.4 Relative Operating Costs w.r.t Network Length

After looking at how density affected the relative operating costs when network length is set constant, we examined how the relative operating costs of different modes vary with network length when traffic density is set constant. In other words, we now analysed how network length affected the relative operating costs. Again, we turned the three-dimensional results into two-dimensional ones to clarify them. This time, traffic density was set at several mean values. We were then able to observe the relative cost behaviour w.r.t network length at four density points: namely, the average market density, the average over-ground density, the average monorail density, and the average under-ground density.

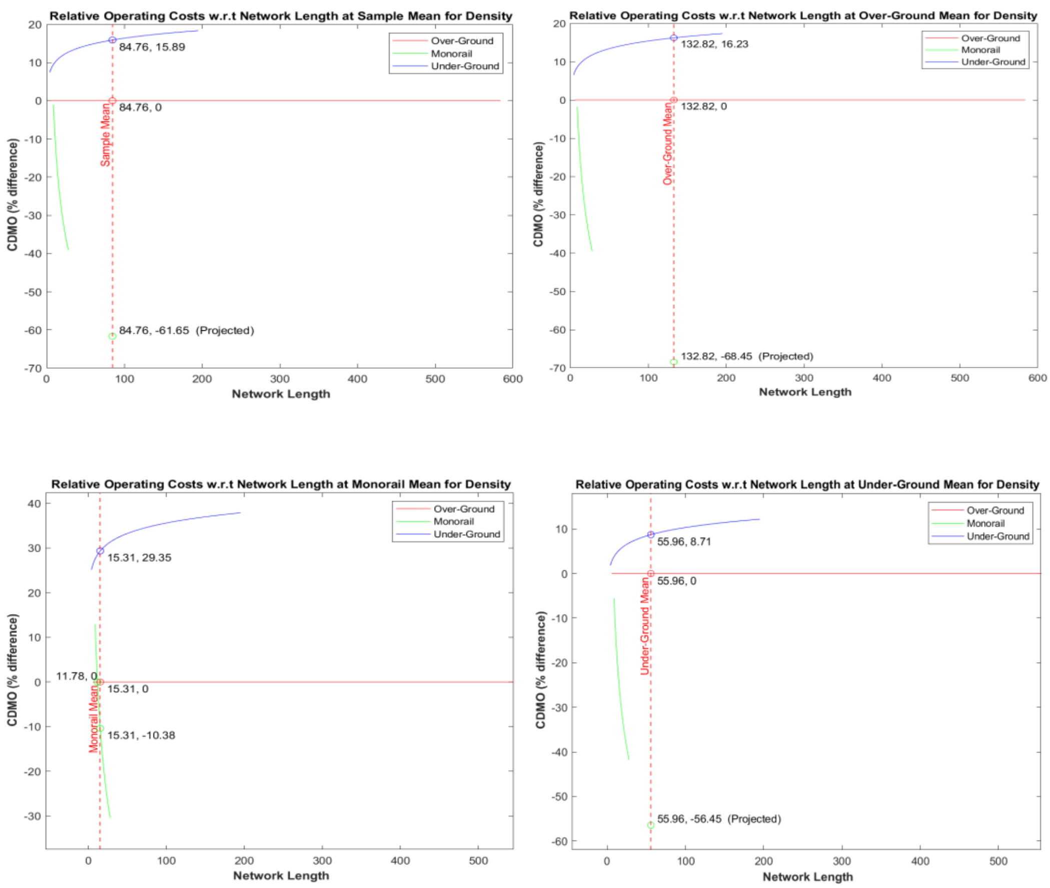
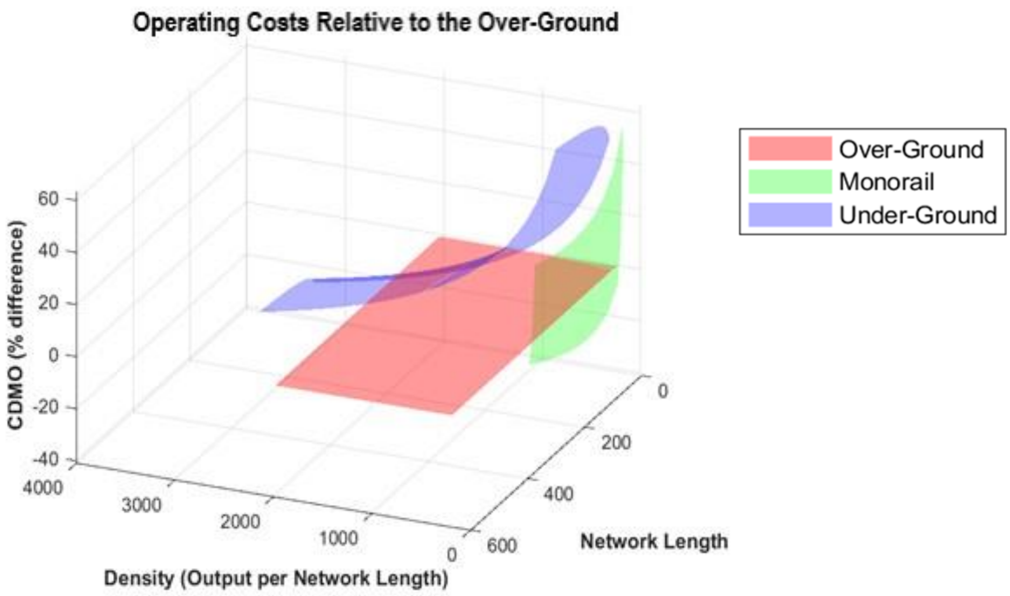


Figure 13. The relative operating costs w.r.t network length; holding density at various means.

Figure 13 on page 99 shows the relative operating costs w.r.t network length for the monorail and the under-ground at various density means (sample, over-ground, monorail, and under-ground means). There are four graphs altogether. They all show similar patterns regarding the relative operating costs for monorail and under-ground. At every density mean, the relative operating costs for the monorail would sharply decrease, whereas the relative operating costs for the under-ground would gradually increase. Monorail will always experience lower costs than the over-ground and the under-ground — except when operating at its average density. At its average density (15.31 car-km per track-km), the lowest among the four density points, the monorail will initially experience higher cost than over-ground before reaching a network length of 11.78 track-km. Based on this evidence, we projected that the monorail would continue to experience decreasing relative operating costs — going as low as 68.45% below the over-ground cost at the latter's average operating density. On the other hand, under-ground will always experience higher costs than over-ground and monorail.

5.3.5 Relative Operating Costs w.r.t Density and Network Length Combinations

We analysed how density and network length affected the relative operating costs. The over-ground was set as the reference mode. Density and network length were allowed to vary within the observed range for each rail mode. By doing so, we could observe the relative costs behaviour w.r.t density and network length combinations. Figure 14 on page 101 shows the relative operating costs w.r.t density and network length combinations for the monorail and the under-ground.



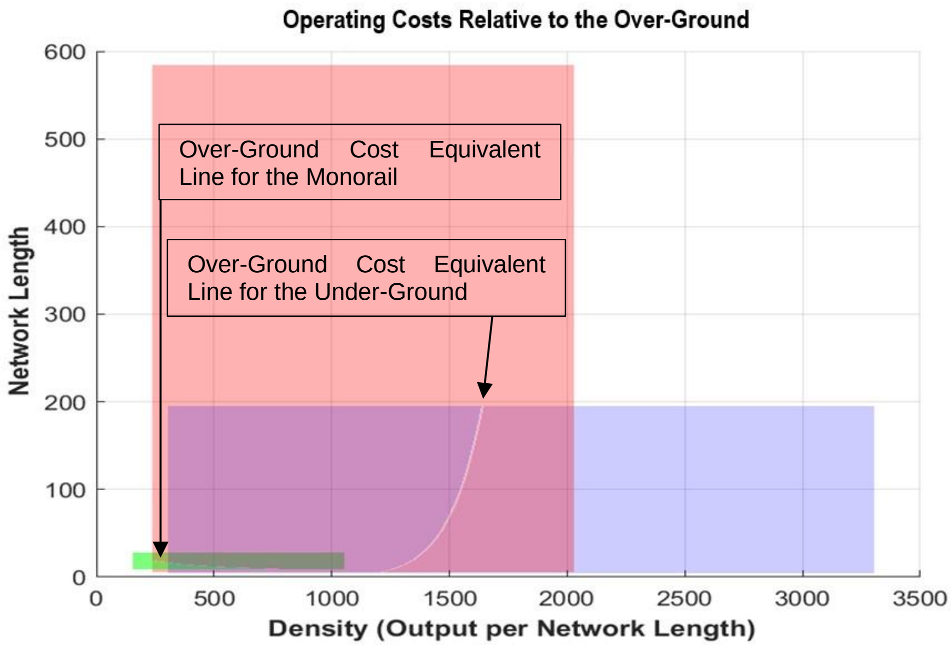


Figure 14. The relative operating costs w.r.t density and network length combinations

The relative operating costs differ at different density and network length combinations. At the minimum combined value of density and network length, the relative costs for monorail can be close to 60% higher than that of the over-ground. At the maximum combined value, the relative costs for monorail can decrease to 40% lower than the over-ground. Likewise, at the minimum combined value, the relative costs for under-ground can be close to 60% higher than that of the over-ground. At the maximum combined value, the relative costs for under-ground can go down to about 20% lower than the over-ground.

The over-ground cost equivalent line for monorail indicated that having a smaller network size would require a higher density (in particular, a higher output volume) — to match the costs of over-ground operation. Referring to Figure 13 on page 99, we found that the average cost of maintaining a smaller network was higher than that of maintaining a more extensive network. A relatively higher output volume (to increase density) was needed to justify the higher average cost.

The over-ground cost equivalent line for under-ground indicated that having a more extensive network size would require a higher density (in particular, a higher output volume) — to match the costs of over-ground operation. Referring to Figure 13 on page 99, we suspect that the average cost of maintaining a more extensive network was higher than that of maintaining a smaller network. A relatively higher output (to increase density) was needed to justify the higher average cost.

There are complex issues around which systems to build in cities, but our work gives information on the operating costs that could be included in the Cost Benefit Analysis (CBA). Specifically, our work shows how the relative operating costs of modes depend on size and density. The answer as to which is best depends on the density and size of the operation desired. For example, under-ground is better than over-ground for 100 track-km of network length and 2000 car-km per track-km of density because of its lower operating costs.

5.3.6 RTD and RTS

Estimating RTD is a key strand of the literature, and this measure is essential. We evaluated whether RTD would differ by mode. Before that, we looked at the CED (see Figure 15 on page 103). We observed that increasing or decreasing the output volume — to change the density — would trigger the cost to change at different rates for different rail modes. In other words, a different rail mode had different CED.

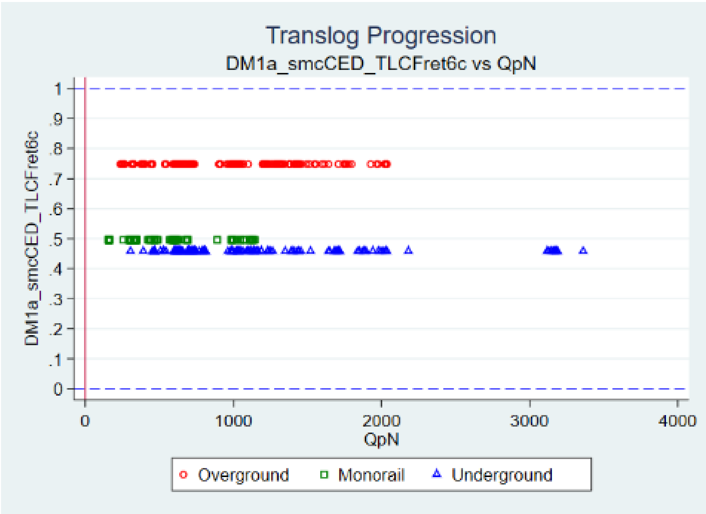


Figure 15. CED by Rail Mode

The CED could be converted to RTD. Table 13 on page 103 is an excerpt of the regression results from Model 6 RE +Time (after purging). The excerpt shows the coefficients involved in calculating the differences between rail modes in RTD.

Table 13. Excerpt of the Regression Results from Model 6 RE +Time (after purging)

Variables	*Coefficient*
$LnmcQpN\ or\ \boldsymbol{\beta}_{\boldsymbol{D}_t}$	0.7490696
$LnmcQpN\_DMM\ or\ \boldsymbol{\beta}_{\boldsymbol{D}_t\boldsymbol{D}_{MM}}$	-0.2523734
$LnmcQpN\_DMU\ or\ \boldsymbol{\beta}_{\boldsymbol{D}_t\boldsymbol{D}_{MU}}$	-0.290507

Where $\boldsymbol{\beta}_{\boldsymbol{D}_t}$ is the coefficient for density (car-km per track-km), $\boldsymbol{D}_{MM}$ is mode dummy for the monorail, and $\boldsymbol{D}_{MU}$ is the mode dummy for the under-ground. We calculated RTD for each rail mode as follows:

$$RTD_{D_{MO}} = \left[\beta_{D_t}\right]^{-1} = \frac{1}{0.7490696} = 1.335 \tag{14}$$

$$RTD_{D_{MM}} = \left[\beta_{D_t} + \beta_{D_t D_M}\right]^{-1} = \frac{1}{0.7490696 - 0.2523734} \\ = 2.013 \tag{15}$$

$$RTD_{D_{MU}} = \left[\beta_{D_t} + \beta_{D_t D_{MU}}\right]^{-1} = \frac{1}{0.7490696 - 0.290507} \\ = 2.181 \tag{16}$$

Among the three, under-ground has the highest RTD (at 2.181), followed by monorail (at 2.013) and over-ground (at 1.335). However, there was no significant difference between the monorail and the under-ground. Note that the values of all RTDs were all above one. It means that a density increase would favour all the rail modes in terms of experiencing lower average cost as the output rises — albeit at different rates.

We concluded that in Japan, the cost structures of all rail modes are conducive to density increase (i.e., increasing RTD). It means that subject to capacity constraints, the operators will experience a lesser average cost when they produce more outputs in the future while maintaining their current network size.

Like RTD, we evaluated whether RTS would differ by mode. Before that, we looked at the CES (see Figure 16 on page 105). We observed that as the network size increased, the cost would change at different rates for different rail modes. In other words, a different rail mode had a different CES.

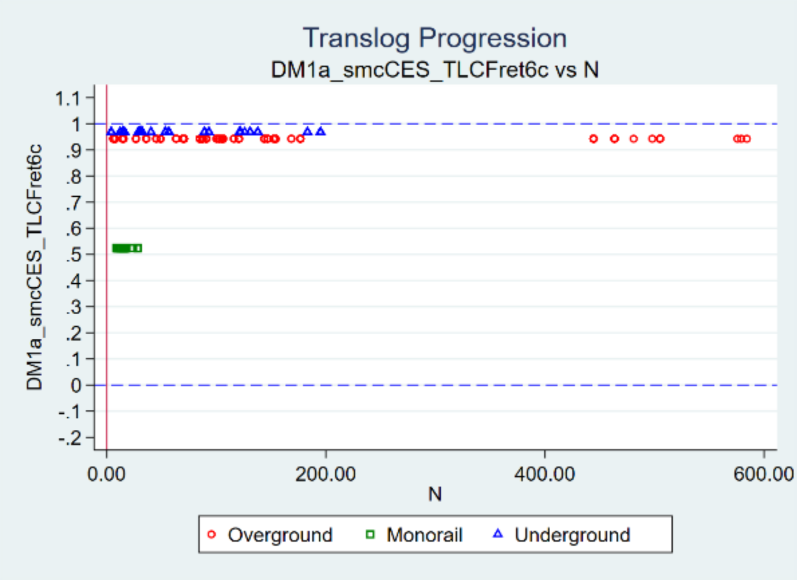


Figure 16. CES by Rail Mode

The CES could be converted to RTS. Table 14 on page 105 is an excerpt of the regression results from Model 6 RE +Time (after purging). The excerpt shows the coefficients in calculating the differences between rail modes in RTS.

Table 14. Excerpt of the Regression Results from Model 6 RE +Time (after purging)

Variables	*Coefficient*
LnmcN or $\boldsymbol{\beta_N}$	0.9430847
LnmcN_DMM or $\boldsymbol{\beta_{ND_{MM}}}$	-0.4184442
LnmcN_DMU or $\boldsymbol{\beta_{ND_{MU}}}$	0.0251065

Where β_N is the coefficient network length (track-km), D_{MM} is mode dummy for the monorail, and D_{MU} is the mode dummy for the underground. We calculated RTS for each rail mode as follows:

$$RTS_{D_{MO}} = [\,\beta_N]^{-1} = \frac{1}{0.9430847} = 1.060 \tag{17}$$

$$RTS_{D_{MM}} = \left[\,\beta_N + \ \beta_{ND_{MM}}\right]^{-1} \tag{18}$$
$$= \frac{1}{0.9430847 - 0.4184442} = 1.906$$

$$RTS_{D_{MU}} = \left[\,\beta_N + \ \beta_{ND_{MU}}\right]^{-1} = \frac{1}{0.9430847 + 0.0251065} \tag{19}$$
$$= 1.033$$

Among the three, the monorail has the highest RTS (at 1.906), followed by over-ground (at 1.060) and under-ground (at 1.033). However, there was no significant difference between over-ground and under-ground. Furthermore, at 95% confidence, we could not say that the RTS value — for each over-ground and under-ground — significantly differed from one (unity). Therefore, a scale increase would not necessarily favour over-ground or under-ground in terms of experiencing lower average cost. On the other hand, the RTS value for the monorail was significantly above one (unity). Therefore, a scale increase would favour the monorail experiencing lower average costs. In short, over-ground and under-ground show constant RTS, while monorail exhibits increasing RTS.

We concluded that in Japan, the cost structure of monorail is conducive to servicing more expansive geographical areas. In comparison, over-ground and under-ground cost structures are not necessarily conducive to servicing more expansive geographical areas. Subject to capacity constraints, monorail operators will experience lesser average costs when they operate on a broader network. Over-ground and under-ground operators will not necessarily experience lesser average costs when they operate on a broader network.

Many authors, including Keeler (1974), Savage (1997), Mizutani (2004), Graham (2008) and Brage-Ardao et al. (2015) found rail services (including urban rails) exhibit increasing RTD but constant

RTS. Our findings are like theirs, with two exceptions. First, we discovered that each urban rail mode (i.e., over-ground, monorail, and under-ground) has its rate of increasing RTD. Under-ground has the highest RTD (at 2.181), followed by monorail (at 2.013) and over-ground (at 1.335). However, there is no significant difference between monorail and under-ground. Second, we discovered that monorail shows increasing RTS while over-ground and under-ground show constant RTS. Monorail has the highest RTS (at 1.906), followed by over-ground (at 1.060) and under-ground (at 1.033). However, there is no significant difference between over-ground and under-ground. All in all, our findings suggest that urban rail modes are different regarding economies of density and scale characteristics in one way or another.

5.4 Discussion

Although the differences between urban rail modes were established as early as 1997, they were often not accounted for in the subsequent urban rail studies. In Japan, where there have been studies on the cost differences by ownership — such as the one conducted by Mizutani (2004), there has never been a study on the cost differences by urban rail mode. Our findings from this study indicated that urban rail modes in Japan differed in operating costs. These findings are in tandem with those of Savage (1997), who focused on the cost of operating urban rail modes in the United States. Considering the findings by Graham (2008), Ingvardson and Nielsen (2018), Min et al. (2017), and Tsai et al. (2015) — who found urban rail modes also differed in the aspect of production, we recommend stating and recognising mode difference in future urban rail studies.

As an extension to the current literature, we have demonstrated how the operating costs would vary between urban rail modes under different traffic density and network length combinations. Under certain combinations, the cost of operating an urban rail mode could become lesser than another. This finding could be a helpful insight to the policymakers in making certain decisions such as the following.

Knowing the expected mixture of traffic density and network length for a new urban rail project helps policymakers decide which rail mode has the least operating costs. Also, projecting future network expansions for the urban rail services will allow policymakers to weigh which rail mode would eventually be the least costly. Together with the infrastructure cost, the projected demand, and other relevant details, the projection of the operating costs could be incorporated into the cost-benefit analysis[8]. This enhancement will help policymakers making better decisions on which rail mode to construct.

Likewise, for any proposal of the current network expansion, the expected mixture of density and network length could indicate whether the cost of operating the expanded urban rail network will be more than, equal to, or less than another. Considering this aspect when exercising the cost-benefit analysis would allow the policy makers to determine whether it is worth proceeding with the desired network expansion. It would be helpful, especially when choosing between two network expansion proposals.

Savage (1997) suggested comparing the marginal cost per passenger mile with the fare per passenger mile to observe whether a particular system can pass on the operating costs in prices. Although our study did not include such calculations, the variation in operating costs relative to various traffic density and network length combinations — demonstrated in our research — should indicate whether the pricing of a particular urban rail service is cost-wise reasonable compared to another urban rail service. We acknowledge that determining fares is not solely based on the operating costs. The passenger demand and

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[8] Although there may be issues to incorporate the projection on operating costs into the cost-benefit analysis — such as how long the projection should be, we opine that taking this initiative is better than otherwise. Consider a scenario when one plans to buy a car. Not only will he evaluate the price of a car, but he will also assess the cost of maintaining the car.

the ‘political pressures’ may also come into play (Savage, 1997, p. 472).

In Japan, one of the significant reforms in 1997 was introducing the ceiling price system. It replaced the price cap regulation, which used the deflator of the consumer price index. The ceiling price used "each individual railway company's full cost level and must be approved by the regulator" (Mizutani & Uranishi, 2013, p. 8). The succeeding reform, which took place in 2000, introduced fare deregulation. The operators could set fares. Fare approval is only required when the ceiling price is exceeded. Our study provides a general picture to Japanese regulators of how the ceiling price could vary across urban rail modes while considering the relevant operator's full cost level. Also, as mentioned earlier, our approach of including the mode effect into the cost function model could make yardstick competition in Japan more accurate, allowing for a more comprehensive application[9].

In Japan, efforts have been made to introduce more urban rail players to liberalise the market. The permission system introduced in 2000 encourages potential new entries — balancing the demand and supply was no longer considered, and the exit regulations were eased. Despite this, Mizutani and Uranishi (2013, p. 16) opined that "competition for entry into the rail market and competition within the market among rail operators is almost unheard of in Japan, where an indirect competition policy such as yardstick regulation is adopted instead". Although a few firms operate services on another company's track, they predominantly cooperate in providing more convenient rail services. There is competition between lines and firms on some of the most essential routes between cities (F. Mizutani, 1997). However, such competition is uncommon. For example, urban rail operations in Tokyo are considered regionally monopolistic (Kato, 2016). We believe the larger over-ground and under-ground systems could be divided into smaller scales to encourage competition. The constant

[9] Yardstick competition is currently being imposed on several rail operators.

RTS for the over-ground and the under-ground — found in our analyses — suggest that the cost disadvantage to breaking up the network span into smaller sizes would be negligible. Our findings on operating costs w.r.t density and network length could be useful if it was decided to use competitive tendering in which case a decision would be needed on what size the franchises would need to be.

5.5 Conclusion

We concluded that this study has met its aims and objectives. It has provided a deeper understanding of the cost structure of each urban rail mode in Japan and the differences between them. This study shows that operating costs vary between modes, with a significant difference. Our findings also suggest that urban rail modes differ regarding economies of density and scale characteristics in one way or another. To be precise, we found that over-ground, monorail, and under-ground have their rate of increasing RTD, although there is no significant difference between monorail and under-ground. We further discovered that monorail shows increasing RTS while over-ground and under-ground show constant RTS. Our findings add value to the current literature in which studies like Keeler (1974), Savage (1997), Mizutani (2004), Graham (2008) and Brage-Ardao et al. (2015) generally found rail services (including urban rails) exhibit increasing RTD but constant RTS. We further learnt that the operating costs vary with the combination of density and network length — and for each urban rail mode, the variation is not the same. Besides that, we found that the results from an econometric tool differed from those from the simple ratio statistics. We concluded that the results derived from an econometric tool are more reliable.

Our findings on urban rail mode differences are consistent with those of Savage (1997), who examined the operational costs of urban rail modes in the United States. Given the findings of Graham (2008), Ingvardson and Nielsen (2018), Min et al. (2017), and Tsai et al. (2015) — all of which discovered that urban rail modes differed in terms of production — we advocate mentioning and identifying mode difference in future urban rail studies.

We have identified several policy implications. First, the expected operating costs could be included in the cost-benefit analysis with the infrastructure cost, projected demand, and other relevant details. This enhancement will aid in making a more informed decision on which rail mode to build. Second, our model and results can be referred to by transport authorities and firms for cost-forecasting purposes. Third, our study provides Japanese regulators with a broad view of how the ceiling price could vary between urban rail modes while accounting for the full cost level of the relevant operator. Fourth, since Japan's yardstick competition utilises the cost function, the mode effect could be integrated into the model for more accurate outcomes. Finally, our model can also help consider how to organise franchises if a competitive tendering technique is used, as it will reveal the best size of the franchise.

We believe that policymakers, regulators, and stakeholders would be able to make more informed decisions on policies, regulations and future investments in urban rail services when equipped with a deeper understanding of the cost structures of urban rail modes. In the regions where cost function studies are rare — especially in the urban rail sector, we anticipate that more cooperation between regulators and industry players will be geared towards identifying and gathering the essential data.

For a more conclusive understanding of cost differences between urban rail modes, we suggest that this empirical research be replicated in other regions where sufficient data is available. It would be interesting to know whether the findings would be similar. In addition, we hope to get more clarity on the RTD and the RTS of the urban rail modes from future empirical research. We foresee that the differences in urban rail mode definitions between regions will be challenging in summing up the current and future empirical findings.

Table 15. Model 6 RE +Time Regression Results (after purging)

```
Random-effects GLS regression                   Number of obs     =        552
Group variable: id                              Number of groups  =         46

R-sq:                                           Obs per group:
     within  = 0.7413                                         min =         12
     between = 0.9742                                         avg =       12.0
     overall = 0.9728                                         max =         12

                                                Wald chi2(17)     =    3493.55
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000
```

LnmcCELMpmcPM	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Time	-.0064877	.0010459	-6.20	0.000	-.0085375	-.0044378
LnmcQpN	.7490696	.056358	13.29	0.000	.63861	.8595292
LnmcQpN_DMM	-.2523734	.1056724	-2.39	0.017	-.4594874	-.0452593
LnmcQpN_DMU	-.290507	.0832885	-3.49	0.000	-.4537494	-.1272646
LnmcPEpmcPM	.1612759	.0217122	7.43	0.000	.1187208	.2038311
LnmcPLpmcPM	.4950746	.0255158	19.40	0.000	.4450645	.5450847
LnmcPMpmcPM	0	(omitted)				
LnmcN	.9430847	.0333984	28.24	0.000	.877625	1.008544
LnmcN_DMM	-.4184442	.1186433	-3.53	0.000	-.6509807	-.1859076
LnmcN_DMU	.0251065	.0570915	0.44	0.660	-.0867907	.1370037
LnmcQpNLnmcN	.1300572	.0354513	3.67	0.000	.0605739	.1995404
LnmcPEpmcPMLnmcPLpmcPM	.2360141	.0463818	5.09	0.000	.1451076	.3269207
LnmcPEpmcPMLnmcPMpmcPM	0	(omitted)				
LnmcPLpmcPMLnmcPMpmcPM	0	(omitted)				
halfLnmcPEpmcPM2	-.1945434	.050584	-3.85	0.000	-.2936861	-.0954007
halfLnmcPLpmcPM2	-.1243123	.0522893	-2.38	0.017	-.2267975	-.0218272
halfLnmcPMpmcPM2	0	(omitted)				
LnmcNLnmcPEpmcPM	-.0386899	.0123049	-3.14	0.002	-.062807	-.0145729
LnmcNLnmcPLpmcPM	.1233431	.0149579	8.25	0.000	.0940262	.15266
LnmcNLnmcPMpmcPM	0	(omitted)				
DMM	-.9584722	.2188037	-4.38	0.000	-1.38732	-.5296249
DMU	.1475098	.0758003	1.95	0.052	-.0010561	.2960757
_cons	.0073412	.0434008	0.17	0.866	-.0777228	.0924053
sigma_u	.16828347					
sigma_e	.04938309					
rho	.92071368	(fraction of variance due to u_i)				

Note: Refer to Table 51 on page 230 for Regression Term Descriptions.

Chapter 6 Research Study 2: Exploring the Ownership Effect on Cost Efficiency

6.1 Introduction

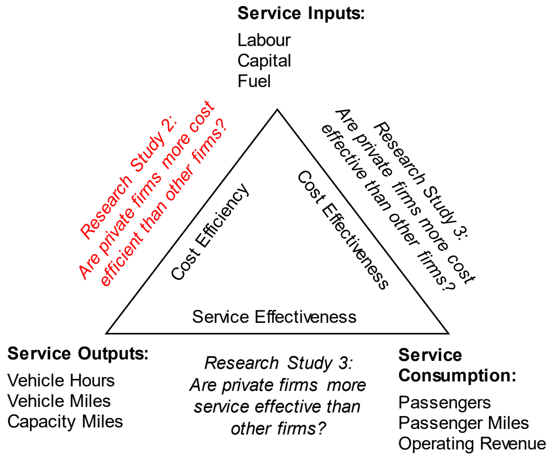
In Chapter 2: The Performance of Private Firms section, we elaborated on how private firms are theoretically expected to perform in the urban rail market. Theoretically, private firms are expected to be more cost-efficient, service-effective, and cost-effective than other firms (see Chapter 2: The Performance of Private Firms section). In this research study (Chapter 6), we are motivated to explore whether private firms in the Japanese urban rail sector are more cost-efficient than other firms (Figure 17 on page 113). The remaining aspects (service effectiveness and cost effectiveness) will be studied in Research Study 3.

Theoretical Expectations

Private firms maximise profit by maximising cost effectiveness. Assuming adjustment on service output is limited, private firms maximise cost effectiveness by maximising cost efficiency and maximising service effectiveness.

Therefore, private firms are expected to be superior in:

- Cost Efficiency;
- Service Effectiveness; and
- Cost Effectiveness.



Source: Fielding et al. (1985) with modification

Figure 17. Theoretical Expectations on the Performance of Private Firms (Research Study 2)

Additionally, in Chapter 2: Cost Efficiency section, we identified three gaps in the literature. First, although we have selected studies that are consistent in their efficiency definition (i.e. following the definition provided by Fielding et al. (1985)), we find these studies have different samples, periods, and efficiency types[1]. It might be why they produced different findings on the private firms' performance in cost efficiency. Given the same sample in the same period, we are motivated to explore whether the ownership effect differs with different efficiency types (i.e., cost efficiency and technical efficiency). Second, the ownership effect on cost efficiency can also be measured using a DEA-Tobit regression besides a trans-log cost function. Given the same sample in the same period, we are motivated to explore whether the ownership effect on cost efficiency differs with different methods. Third, we are unaware of any study that accounts for the mode effect when assessing the ownership effect on efficiency in the urban rail sector. Therefore, we are also motivated to include the mode effect in the models when exploring the ownership effect on efficiency in the Japanese urban rail sector.

We applied two methods in this study. One is the trans-log cost function, and another is the DEA-Tobit regression.

For the trans-log cost function, we utilised the model from Research Study 1 and added the ownership variable. It served two purposes. First, we want to observe whether adding the ownership variable would significantly alter the results in Research Study 1. Doing so tests the robustness of our model. Second, we want to compare the results from a trans-log cost function model against those from a DEA-Tobit regression model.

For DEA-Tobit regression, we first conducted DEA to produce cost efficiency scores and technical efficiency scores. We set the following specifications when running DEA:

[1] Cost efficiency and technical efficiency.

Type of score	*Input for DEA*	*Output for DEA*
Cost efficiency	C_{ELM} (Yen)	Q (thousand car-km)
Technical efficiency	energy (kWh), labour (persons), rolling stock (unit)	Q (thousand car-km)

We applied input orientation DEA since we assumed firms are expected to provide reliable routine services, limiting their service output adjustment. Other authors who have used input orientation include Kerstens (1996) and Tsai et al. (2015). After obtaining DEA cost efficiency scores and DEA technical efficiency scores, we performed Tobit regression. We specified the efficiency scores as the dependent variable in two separate regressions (i.e., cost efficiency in one regression and technical efficiency in another). We then selected D_t (car-km/operating-km), N (operating-km), DM_{MR} (dummy for monorail), DM_{UG} (dummy for under-ground), DO_B (dummy for private firms), and T (year) as the independent variables.

Note that the network DEA method is different from the standard DEA method. Convexity constraint is not present in the network DEA method since the multiplier and envelopment models are not equivalent (or dual) under the network DEA (Chen et al., 2014; Zhang et al., 2021; Zhu, 2020). Therefore, we cannot measure efficiency using the network DEA[2].

6.2 Objectives

We aim to explore the ownership effect on cost efficiency in the Japanese urban rail sector. In doing so, we set the following objectives:

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[2] The network DEA method is relatively new and still undergoing development. We prefer to utilise the standard DEA method which has been established in the literature.

a. determine whether adding the ownership variable into Research Study 1’s trans-log cost function model does not materially change the coefficients elsewhere,
b. explore whether different methods (i.e., trans-log cost function and DEA-Tobit regression) would yield similar results, and
c. determine whether private firms are more cost-efficient than other firms.

6.3 Results and Discussion

This section is divided into three subsections. The first subsection compares and evaluates the results from the trans-log cost function model used in Research Study 1 against those from the trans-log cost function model used in Research Study 2. Both are parametric models. The difference is that we added the ownership variable into the latter to evaluate the ownership effect on efficiency. There could be some correlation between ownership and mode, and we want to inspect how adding ownership changes the other coefficients in the model. Thus, in addition to providing new information on the impact of ownership on costs and efficiency, we can study ownership and mode effects together and check the robustness of Research Study 1’s findings to the addition of ownership effects.

The second subsection compares and evaluates the results from the DEA-Tobit regression model against those from the trans-log cost function model used in this study (Research Study 2). The former is semi-parametric, while the latter is parametric. They are two widely used methods for deriving performance, especially efficiency. The purpose is to evaluate whether there is any difference between the results. DEA-Tobit regression and trans-log cost function are two different approaches. Perry et al. (1988) mentioned that different analytical methods may cause inconsistent results. We will inspect how ownership, density, scale, mode, and time affect:

a. operating costs in the trans-log cost function model,
b. cost efficiency in the DEA-Tobit regression model, and

c. technical efficiency in the DEA-Tobit regression model.

The third subsection will discuss private firms' cost, cost efficiency and technical efficiency performance in the Japanese urban rail sector.

6.3.1 Results Comparison between the Trans-log Cost Function Model in Research Study 1 and the Trans-log Cost Function Model in Research Study 2

We found that, in general, the results from the trans-log cost function model used in Research Study 1 (Chapter 5) were almost the same as the results from the trans-log cost function model used in Research Study 2 (this chapter) — except for the ownership variable that did not exist in the former. Table 16 on page 117 presents an excerpt from the trans-log cost function regression results (for Research Study 1 and Research Study 2).

Table 16. Excerpt from Trans-log Cost Function Regression Results (for Research Study 1 and 2)

Factor of interest			**Research Study 1**	**Research Study 2**
CED	O	Coef.	0.749	0.754
		Sig.	0.000	0.000
	M	Coef.	0.497	0.382
		Sig.	0.002	0.001
	U	Coef.	0.459	0.388
		Sig.	0.000	0.000
CES	O	Coef.	0.943	0.912
		Sig.	0.000	0.000
	M	Coef.	0.525	0.480
		Sig.	0.000	0.000

Factor of interest			Research Study 1	Research Study 2
	U	Coef.	0.968	0.936
		Sig.	0.000	0.000
Cost Difference between Modes[3]	M v O	Diff.	(0.617)	(0.532)
		Sig.	0.000	0.001
	U v O	Diff.	0.159	0.556
		Sig.	0.052	0.002
	U v M	Diff.	2.022	2.325
		Sig.	0.000	0.000
Time Effect		Coef.	(0.006)	(0.006)
		Sig.	0.000	0.000
Cost Difference between Ownership[4]	Private v Others	Diff.		0.429
		Sig.		0.013

Note: O = over-ground; M = monorail; U = under-ground. Brackets represent a negative value.

[3] Cost difference between modes is derived by $x = e^{(\beta_{DM})} - 1$. Multiplying *x* by 100, the interpretation for the trans-log cost function model will be "the operating costs for Mode A are *x* per cent more than the operating costs for over-ground (omitted variable)". Brackets represent a negative value. In this case, the interpretation will be "the operating costs for Mode A are *x* per cent less than the operating costs for over-ground". Cost difference between under-ground and monorail is derived by $x = e^{\left(\beta_{DM_U} - \beta_{DM_M}\right)} - 1$.

[4] Cost difference between ownerships is derived by $x = e^{(\beta_{DO})} - 1$. Multiplying *x* by 100, the interpretation for the trans-log cost function model will be "the operating costs for private firms are *x* percent more than the operating costs for other firms (omitted variable)". Brackets represent a negative value. In this case, the interpretation will be "the operating costs for private firms are *x* percent less than the operating costs for other firms".

6.3.1.1 CED

At 1% significance level, the CED for over-ground is 0.749 in Research Study 1 and 0.754 in Research Study 2. The CED for monorail is 0.497 in Research Study 1 and 0.382 in Research Study 2. The CED for under-ground is 0.459 in Research Study 1 and 0.388 in Research Study 2.

With 95% confidence, it can be said that the CED remains significant for each mode[5]. Each mode still experiences increasing RTD — albeit at an individual rate.

6.3.1.2 CES

At 1% significance level, the CES for over-ground is 0.943 in Research Study 1 and 0.912 in Research Study 2. The CES for monorail is 0.525 in Research Study 1 and 0.480 in Research Study 2. The CES for under-ground is 0.968 in Research Study 1 and 0.936 in Research Study 2.

With 99% confidence, it can be said that the CES remains significant for each mode[6]. Each mode still experiences increasing RTS — albeit at an individual rate. Note that over-ground and under-ground still have values below unity in Research Study 2, albeit a little smaller than before.

6.3.1.3 Cost Difference between Modes

At 1% significance level, the operating costs for the monorail are 61.7% less than the operating costs for over-ground in Research Study 1. It is 53.2% less than the over-ground in Research Study 2. At 6% significance level, the operating costs for under-ground are 15.9% more than those for over-ground in Research Study 1. It is 55.6% more than the operating costs for over-ground in Research Study 2. At 1% significance level, the operating costs for under-ground are 202.2%

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[5] at the sample mean
[6] at the sample mean

more than the operating costs for the monorail in Research Study 1. It is 232.5% more than the operating costs for the monorail in Research Study 2.

With 94% confidence, it can be said that the cost difference between modes remains significant. Monorail remains to have the least operating cost, consecutively followed by the over-ground and the under-ground.

6.3.1.4 Time Effect

At 1% significance level, operating costs will decrease by 0.006% from year to year in Research Studies 1 and 2. With 99% confidence, it can be said that the time effect remains significant. Time improves (reduces) operating costs by 0.006%.

6.3.1.5 Cost Difference between Ownership

At 2% significance level, the operating costs for private firms are 42.9% more than those for other firms in Research Study 2. With 99% confidence, it can be said that the ownership effect is significant. There is a significant difference in operating costs between private firms and others — with private firms incurring more operating costs than others.

6.3.1.6 Observation

In general, we observed that adding the ownership variable does not materially change the coefficients elsewhere in the trans-log cost function model — except in the cost difference between under-ground and over-ground. Adding the ownership variable causes a larger cost difference between the two modes and a slightly better degree of significance. Overall, we concluded that the trans-log models used in Research Studies 1 and 2 are reliable, and the findings in the previous study still hold.

6.3.2 Results Comparison between the Trans-log Cost Function Model, DEA-Tobit Regression Cost Efficiency Model, and DEA-Tobit Regression Technical Efficiency Model (Research Study 2 Models)

We compared the DEA-Tobit regression model results with the trans-log cost function model. There are five effects from the models we are interested in. They are ownership, density, scale, mode, and time effects. We referred to excerpts from the relevant regression results when discussing. For more detailed results, please refer to:

- Table 22. Trans-log Cost Function Regression Results (Model for Research Study 1) on page 138,
- Table 23. Trans-log Cost Function Regression Results (Model for Research Study 2) on page 139,
- Table 24. DEA-Tobit Regression Results for Cost Efficiency (CRS) on page 140,
- Table 25. DEA-Tobit Regression Results for Cost Efficiency (VRS) on page 141,
- Table 26. DEA-Tobit Regression Results for Technical Efficiency (CRS) on page 142, and
- Table 27. DEA-Tobit Regression Results for Technical Efficiency (VRS) on page 143.

6.3.2.1 Ownership Effect

Table 17 on page 122 presents the ownership effect generated by the Trans-log Cost Function (TLCF), DEA-Tobit Regression Cost Efficiency, and DEA-Tobit Regression Technical Efficiency Models. The TLCF model shows that at a 2% significance level, the operating costs for private firms are 42.9% less than those for other firms. The DEA-Tobit models show that:

- at 3% significance level, the CRS cost efficiency for private firms is 43.4% less than the cost efficiency for other firms,

- at 11% significance level, the VRS cost efficiency for private firms is 24.4% less than the cost efficiency for other firms,
- at 1% significance level, the CRS technical efficiency for private firms is 47.5% less than the technical efficiency for other firms, and
- at 1% significance level, the VRS technical efficiency for private firms is 38.2% less than the technical efficiency for other firms.

Table 17. Ownership Effect Generated by the Trans-log Cost Function, DEA-Tobit Regression Cost Efficiency, and DEA-Tobit Regression Technical Efficiency Models

		MODEL				
Factor of interest		**TLCF**	**DEA-Tobit Cost Efficiency**		**DEA-Tobit Tech. Efficiency**	
			CRS	**VRS**	**CRS**	**VRS**
Ownership Effect[7] (Private v Others)	Diff.	0.429	(0.434)	(0.244)	(0.475)	(0.382)
	Sig.	0.013	0.022	0.105	0.000	0.000

Note: TLCF = Trans-log Cost Function. Brackets represent a negative value. Other firms consist of public and quasi-public firms.

The TLCF model shows the effect on cost, while the DEA-Tobit models show the effect on efficiency. A negative value on the TLCF model is equivalent to a positive value on the DEA-Tobit models.

All models show that ownership significantly affects cost, cost efficiency, and technical efficiency. The DEA-Tobit model for VRS cost efficiency shows a strong confidence level (89%), while other models show much stronger confidence levels (at least 97%).

Albeit at varying degrees (ranging from 24.4% to 43.4%), all models are consistent in showing that private ownership negatively affects

[7] Ownership effect is derived by $x = e^{(\beta_{DO})} - 1$. Multiplying *x* by 100, the interpretation for the TLCF model will be "the operating costs for private firms are *x* percent more than the operating costs for other firms (omitted variable)". Brackets represent a negative value. In this case, the interpretation will be "the operating costs for private firms are *x* percent less than the operating costs for other firms". For the DEA-Tobit model, the term 'operating costs' is replaced by 'cost efficiency' or 'technical efficiency' — whichever is applicable.

cost (increases cost), cost efficiency (decreases cost efficiency), and technical efficiency (decreases technical efficiency). The trans-log cost function model shows that private firms have higher operating costs than other firms — other things being equal (i.e., holding output constant). Correspondingly, the DEA-Tobit regression models show that private firms have a lower cost efficiency and technical efficiency than other firms. All models suggest that private firms are weaker than other firms concerning cost, cost efficiency, and technical efficiency.

6.3.2.2 Density Effect

Table 18 on page 124 shows the density effect generated by the Trans-log Cost Function, DEA-Tobit Regression Cost Efficiency, and DEA-Tobit Regression Technical Efficiency Models. The TLCF model shows that at 1% significance level,

- the CED for over-ground is 0.754,
- the CED for monorail is 0.382, and
- the CED for under-ground is 0.388.

The DEA-Tobit models show that at 1% significance level,

- CRS cost efficiency will increase by 0.471% given a percentage increase in density,
- VRS cost efficiency will increase by 0.453% given a percentage increase in density,
- CRS technical efficiency will increase by 0.592%, given a percentage increase in density, and
- VRS technical efficiency will increase by 0.627%, given a percentage increase in density.

Table 18. Density Effect Generated by the Trans-log Cost Function, DEA-Tobit Regression Cost Efficiency, and DEA-Tobit Regression Technical Efficiency Models

Factor of interest			TLCF	DEA-Tobit Cost Efficiency CRS	DEA-Tobit Cost Efficiency VRS	DEA-Tobit Tech. efficiency CRS	DEA-Tobit Tech. efficiency VRS
CED	O	Coef.	0.754				
		Sig.	0.000				
	M	Coef.	0.382				
		Sig.	0.001				
	U	Coef.	0.388				
		Sig.	0.000				
Density Effect on Cost Efficiency		Coef.		0.471	0.453		
		Sig.		0.000	0.000		
Density Effect on Technical Efficiency		Coef.				0.592	0.627
		Sig.				0.000	0.000

Note: TLCF = Trans-log Cost Function (Research Study 2); O = over-ground; M = monorail; U = under-ground.

All models show that density significantly affects cost, cost efficiency, and technical efficiency. They show very strong confidence levels (at least 99%). Not only that, but they also consistently show how density affects cost, cost efficiency, and technical efficiency. The trans-log cost function model shows that the CED is between zero and unity for all rail modes: 0.754 for over-ground, 0.382 for the monorail, and 0.388 for under-ground. These results suggest that operating costs are inelastic to a density increase for all rail modes. A percentage increase in density causes the operating costs to increase at a lesser percentage. This condition is also known as increasing RTD.

Correspondingly, the DEA-Tobit regression models show density improves cost efficiency and technical efficiency. All models suggest that a higher density brings cost, cost efficiency, and technical efficiency advantages. These findings on density are similar to those of Research Study 1 (Chapter 5).

6.3.2.3 Scale Effect

Table 19 on page 125 presents the scale effect generated by the Trans-log Cost Function, DEA-Tobit Regression Cost Efficiency, and DEA-Tobit Regression Technical Efficiency Models. The TLCF model shows that at 1% significance level,

- the CES for over-ground is 0.912,
- the CES for monorail is 0.480, and
- the CES for under-ground is 0.936.

The DEA-Tobit models show that at 2% significance level,

- CRS cost efficiency will increase by 0.185%, given a percentage increase in scale,
- VRS cost efficiency will increase by 0.239%, given a percentage increase in scale,
- CRS technical efficiency will increase by 0.104%, given a percentage increase in scale, and
- VRS technical efficiency will increase by 0.215%, given a percentage increase in scale.

Table 19. Scale Effects Generated by the Trans-log Cost Function, DEA-Tobit Regression Cost Efficiency, and DEA-Tobit Regression Technical Efficiency Models

			MODEL				
Factor of interest			**TLCF**	**DEA-Tobit Cost Efficiency**		**DEA-Tobit Tech. Efficiency**	
				CRS	**VRS**	**CRS**	**VRS**
CES	O	Coef.	0.912				

Factor of interest			TLCF	DEA-Tobit Cost Efficiency CRS	DEA-Tobit Cost Efficiency VRS	DEA-Tobit Tech. Efficiency CRS	DEA-Tobit Tech. Efficiency VRS
		Sig.	0.000				
	M	Coef.	0.480				
		Sig.	0.000				
	U	Coef.	0.936				
		Sig.	0.000				
Scale Effect on Cost Efficiency		Coef.		0.185	0.239		
		Sig.		0.003	0.000		
Scale Effect on Technical Efficiency		Coef.				0.104	0.215
		Sig.				0.017	0.000

Note: TLCF = Trans-log Cost Function (Research Study 2); O = over-ground; M = monorail; U = under-ground.

All models show that scale significantly affects cost, cost efficiency, and technical efficiency. They show very strong confidence levels (at least 98%). Also, they consistently show how scale affects cost, cost efficiency, and technical efficiency. The trans-log cost function model shows that the CES is between zero and unity for all rail modes: 0.912 for over-ground, 0.480 for the monorail, and 0.936 for under-ground. For over-ground and monorail, CES is less than unity (with 95% confidence). For under-ground, CES is less than unity (83.4% confidence). These results suggest that operating costs are inelastic to a scale increase for all rail modes. A percentage increase in scale causes the operating costs to increase at a lesser percentage. This condition is also known as increasing RTS. Correspondingly, the DEA-Tobit regression models show scale improves cost efficiency and technical efficiency. All models suggest that a more extensive scale brings cost, cost efficiency, and technical efficiency advantages. These findings on the scale are similar to those of Research Study 1 (Chapter 5).

6.3.2.4 Mode Effect

Table 20 on page 128 presents mode effects generated by the Trans-log Cost Function, DEA-Tobit Regression Cost Efficiency, and DEA-Tobit Regression Technical Efficiency Models. The TLCF model shows that:

- at 1% significance level, the operating costs for monorail are 53.2% less than the operating costs for over-ground,
- at 6% significance level, the operating costs for under-ground are 55.6% more than those for over-ground, and
- at 1% significance level, the operating costs for the under-ground are 232.5% more than the operating costs for the monorail.

The DEA-Tobit models show that:

- at 60% significance level, the CRS cost efficiency for monorail is 12.1% less than the cost efficiency for over-ground,
- at 40% significance level, the VRS cost efficiency for monorail is 18.5% more than the cost efficiency for over-ground,
- at 57% significance level, the CRS technical efficiency for monorail is 8.4% less than the technical efficiency for over-ground,
- at 36% significance level, the VRS technical efficiency for monorail is 12.7% more than the technical efficiency for over-ground,
- at 1% significance level, the CRS cost efficiency for under-ground is 49.2% less than the cost efficiency for over-ground,
- at 1% significance level, the VRS cost efficiency for under-ground is 42.5% less than the cost efficiency for over-ground,

- at 1% significance level, the CRS technical efficiency for under-ground is 38.7% less than the technical efficiency for over-ground,
- at 1% significance level, the VRS technical efficiency for under-ground is 33.6% less than the technical efficiency for over-ground,
- at 1% significance level, the CRS cost efficiency for under-ground is 42.2% less than the cost efficiency for the monorail,
- at 1% significance level, the VRS cost efficiency for under-ground is 51.4% less than the cost efficiency for the monorail,
- at 1% significance level, the CRS technical efficiency for under-ground is 33.1% less than the technical efficiency for the monorail, and
- at 1% significance level, the VRS technical efficiency for under-ground is 41.1% less than for monorail.

Table 20. Mode Effects Generated by the Trans-log Cost Function, DEA-Tobit Regression Cost Efficiency, and DEA-Tobit Regression Technical Efficiency Models

Factor of interest			**MODEL**				
			TLCF	**DEA-Tobit Cost Efficiency**		**DEA-Tobit Tech. Efficiency**	
				CRS	**VRS**	**CRS**	**VRS**
Mode Effect[8]	M v O	Diff.	(0.532)	(0.121)	0.185	(0.084)	0.127
		Sig.	0.001	0.595	0.398	0.570	0.354

[8] Mode effect (or mode difference) is derived by $x = e^{(\beta_{DM})} - 1$. Multiplying x by 100, the interpretation for the TLCF model will be "the operating costs for Mode A are x percent more than the operating costs for over-ground (omitted variable)". Brackets represent a negative value. In this case, the interpretation will be "the operating costs for Mode A are x percent less than the operating costs for over-ground". Mode difference between under-ground and monorail is derived by $x = e^{\left(\beta_{DM_U} - \beta_{DM_M}\right)} - 1$. For the DEA-Tobit model, the term 'operating costs' is replaced by 'cost efficiency' or 'technical efficiency' — whichever is applicable.

Factor of interest		MODEL				
		TLCF	DEA-Tobit Cost Efficiency		DEA-Tobit Tech. Efficiency	
			CRS	VRS	CRS	VRS
U v O	Diff.	0.556	(0.492)	(0.425)	(0.387)	(0.336)
	Sig.	0.002	0.005	0.001	0.000	0.000
U v M	Diff.	2.325	(0.422)	(0.514)	(0.331)	(0.411)
	Sig.	0.000	0.004	0.000	0.005	0.000

Note: TLCF = Trans-log Cost Function (Research Study 2); O = over-ground; M = monorail; U = under-ground. Brackets represent a negative value.

The TLCF model shows the effect on cost, while the DEA-Tobit models show the effect on efficiency. A negative value on the TLCF model is equivalent to a positive value on the DEA-Tobit models.

All models show a significant difference in cost, cost efficiency, and technical efficiency between rail modes (at least 99% confidence level) — except between monorail and over-ground. While there is a significant difference (with 99% confidence level) in cost between monorail and over-ground (as shown by the Cost Function model), there are insignificant differences in cost efficiency and technical efficiency between them (as demonstrated by the DEA-Tobit regression models).

Albeit at varying degrees, all models consistently show that under-ground has a weaker performance than over-ground and monorail in cost, cost efficiency, and technical efficiency. The trans-log cost function model shows that under-ground has higher operating costs than over-ground and monorail. Correspondingly, the DEA-Tobit regression models show that under-ground has a lower cost efficiency and technical efficiency than over-ground and monorail.

Even though the models are inconsistent in showing how performance differs between monorail and over-ground, there is a similarity between the DEA-Tobit regression models and the trans-log cost function model when VRS results of the DEA-Tobit regression models are considered. The DEA-Tobit regression models suggest that monorail has a better cost and technical efficiency than over-ground — although with a confidence level of 60% and 64%, respectively. Correspondingly, the trans-log cost function suggests that monorail has lower operating costs than over-ground (with 99% confidence). It is worth noting that VRS is prevalent in the study of the rail industry (Lan & Lin, 2003; Merkert et al., 2017; Tsai et al., 2015).

All models agree that under-ground has the weakest performance in cost, cost efficiency, and technical efficiency. Suppose VRS results of the DEA-Tobit regression models are considered. In this case, the DEA-Tobit regression and the trans-log cost function models agree that the monorail has the best performance in cost, cost efficiency, and technical efficiency.

6.3.2.5 Time Effect

Table 21 on page 131 presents the time effect generated by the Trans-log Cost Function, DEA-Tobit Regression Cost Efficiency, and DEA-Tobit Regression Technical Efficiency Models. The TLCF model shows that at 1% significance level, operating costs will decrease by 0.006% from one year to another. The DEA-Tobit models show that at 2% significance level,

- CRS cost efficiency will increase by 0.017% from one year to another,
- VRS cost efficiency will increase by 0.005% from one year to another,
- CRS technical efficiency will increase by 0.003% from one year to another, and
- VRS technical efficiency will decrease by 0.002% from one year to another.

Table 21. Ownership Effect and Time Effect Generated by the Trans-log Cost Function, DEA-Tobit Regression Cost Efficiency, and DEA-Tobit Regression Technical Efficiency Models

Factor of interest		**TLCF**	**DEA-Tobit Cost Efficiency**		**DEA-Tobit Tech. Efficiency**	
			CRS	**VRS**	**CRS**	**VRS**
Time Effect	Coef.	(0.006)	0.017	0.005	0.003	(0.002)
	Sig.	0.000	0.000	0.000	0.000	0.015

Note: TLCF = Trans-log Cost Function. Brackets represent a negative value. Other firms consist of public and quasi-public firms.

The TLCF model shows the effect on cost, while the DEA-Tobit models show the effect on efficiency. A negative value on the TLCF model is equivalent to a positive value on the DEA-Tobit models.

All models show that time significantly affects cost, cost efficiency, and technical efficiency (with at least 98% confidence level). Except for the DEA-Tobit regression technical efficiency (VRS) model, they consistently show that time improves cost, cost efficiency, and technical efficiency. The trans-log cost function model shows that operating costs reduce with time. Correspondingly, the DEA-Tobit regression models show that cost efficiency improves with time. The DEA-Tobit regression technical efficiency (CRS) model also indicates that technical efficiency improves with time. However, the DEA-Tobit regression technical efficiency (VRS) model shows technical efficiency declines with time.

6.3.2.6 Observation

We observed that results from the trans-log cost function, the DEA-Tobit Cost Efficiency, and the DEA-Tobit Technical Efficiency models are similar, although not the same.

We also observed that the DEA-Tobit regression cost efficiency models produce more similar results to those of the trans-log cost function model than the DEA-Tobit regression technical efficiency models. In particular, the time effect is identical between the DEA-Tobit regression cost efficiency models and the trans-log cost function model. However, the time effect is only identical between the DEA-Tobit regression technical efficiency (CRS) model and the trans-log cost function model, but not the DEA-Tobit regression technical efficiency (VRS) model.

We further observed that the DEA-Tobit regression cost efficiency (VRS) model produces more similar results to those of the trans-log cost function model than the DEA-Tobit regression cost efficiency (CRS) model. In particular, the performance difference between monorail and over-ground is similar between the DEA-Tobit regression cost efficiency (VRS) model and the trans-log cost function model, but not the DEA-Tobit regression cost efficiency (CRS) model. It is expected since the trans-log cost function also supports VRS.

We concluded that the DEA-Tobit regression cost efficiency (VRS) model produces the most similar results to the trans-log cost function model among the DEA-Tobit regression models.

6.3.3 Discussion

From the models, we are at least 95% confident[9] that private firms performed weaker than other firms in cost, cost efficiency, and technical efficiency – when we hold other factors constant at the sample mean. It is unexpected if we refer to the theoretical explanation in Chapter 2, which expects private firms to perform better than others.

The literature findings are mixed, especially regarding rail and urban rail services. For example, Filippini and Maggi (1993) found that ownership does not affect efficiency in Switzerland, Lan and Lin (2003)

[9] Except for the DEA-Tobit model for VRS cost efficiency, in which we are at least 86% confident.

found that ownership does not affect efficiency from their worldwide study, and Canavan (2015) found that private firms are less efficient than public firms from his worldwide study. It is potentially due to differences in the sample, period, and efficiency type (i.e., cost efficiency and technical efficiency). Perry et al. (1988) stated, “The variety of organisational samples, periods and analytical methods have made comparison of research results difficult.” We attempted to address this issue by assessing private firms’ performance in cost, cost, efficiency, and technical efficiency using the same sample and period, and we found similar results in cost, cost efficiency, and technical efficiency — that is, private firms performed weaker than other firms.

In this study, we have segregated the mode effect from the ownership effect by including both in our model. We observed no significant changes in the coefficients when we added the ownership variable to the model used in Research Study 1, which contains the mode variable[10] — despite finding a degree of correlation between mode and ownership (see Chapter 4). Mizutani (1994, p. 168) found a similar correlation when assessing the cost effectiveness of urban rail services in Japan and noted that this correlation “should not cause bias in the coefficients.”

Our finding on the ownership effect on efficiency in the Japanese urban rail sector differs from Mizutani (2004), who concluded that efficiency does not vary much between private and public firms in the same sector above. Nonetheless, we found two explanations by Mizutani (2004) relevant. Firstly, smaller private firms are regional monopolies, and fare regulation protects them. It makes them have less incentive to minimise service inputs. Secondly, public firms are relatively new, and new technology saves operating costs.

Another possible reason is the diversification strategy adopted by private firms. Under this strategy, private firms develop residential

[10] To recall, we also found that the mode effect on cost to be significant.

areas and leisure facilities near their rail service areas (Shoji, 2005). As much as rail operations internalise externalities from these property developments, the latter internalise externalities from rail operations. We believe that with this interdependency, private firms may have invested in improving their service quality — such as better customer service — for rail and non-rail activities. In doing so, they compromise on cost efficiency, a function of cost and output (car-km).

Other additional factors may have also contributed to this finding. The first one is government intervention when private firms cannot sustain losses. This results in the establishment of quasi-public firms to preserve the unprofitable lines (Saito, 2015; Shoji, 2001). We believe that these precedents tend to alter the behaviour of other private firm managers. They become complacent because they see a safety net that saves them from losing their job when the firm incurs losses. The second one is the behaviour of the quasi-public firms, which faced unprofitable services. Sekiguchi et al. (2010, p. 1286) stated that many of these firms "have found that demand is far less than projected" and are "doing everything in their power to improve their bottom lines". These firms have implemented cost-cutting measures to minimise losses. The third one is the network infrastructure, which is limited for competition since there can only be one train at one route stop at one time. Almost all private rail operators in the Tokyo Metropolitan Area that operated trains in 2015 had their rail network and infrastructure, according to Kato (2016). While some firms may offer services on a track owned by another company, their primary focus is on collaborating to enhance the accessibility of rail services. Competition among lines and firms exists on crucial intercity routes, as noted by F. Mizutani (1997). Nevertheless, the prevalence of such competition is limited. According to Kato (2016), the urban rail operations in Tokyo are regarded as having a regional monopoly.

In an urban rail market, perfect competition and near-perfect competition are almost implausible. Policymakers could not always expect private firms to have better cost efficiency than public firms. Private firms are profit maximising entities, not cost-efficiency maximisers. As illustrated, they would compromise cost efficiency to pursue maximum profit. One example is the urban rail market in Japan — where the eco-system is more complex than the theoretical settings. Private firms are allowed to develop lands that can spur ridership, ensuring the sustainability of their operation.

As much as rail operations internalise externalities from these property developments, the latter internalise externalities from rail operations. We believe that with this interdependency, private firms may have invested in improving their service quality — such as better customer service — for rail and non-rail activities. It raises operating costs, and private firms may have lower cost efficiency[11] than public firms.

6.4 Conclusion

We concluded that this study has met its aims and objectives. The consistent results of adding the ownership effect into the trans-log cost function model used in the previous chapter reaffirm our findings from Research Study 1. In addition, we found that results from the trans-log cost function, the DEA-Tobit Cost Efficiency, and the DEA-Tobit Technical Efficiency models are similar, although not the same. Among the DEA-Tobit regression models (i.e., DEA-Tobit Cost Efficiency CRS, DEA-Tobit Cost Efficiency VRS, DEA-Tobit Technical Efficiency CRS, and DEA-Tobit Technical Efficiency VRS), the DEA-Tobit Cost Efficiency VRS model produced the most similar results to the trans-log cost function model. It is expected since the trans-log cost function also supports VRS.

Furthermore, this study gave us a better grasp of the ownership effect on cost efficiency in the Japanese urban rail sector. We can infer from this study that private firms performed weaker than other firms in cost, cost efficiency, and technical efficiency — when we hold other factors constant at the sample mean. We also know this is true under two

[11] which is a function of cost and output (car-km).

widely used methods for deriving efficiency (i.e., the trans-log cost function and the DEA-Tobit regression).

Considering the theoretical explanation in Chapter 2, which assumes that private firms will outperform the rest, this is unexpected. There are several explanations to our findings. First, smaller private firms are regional monopolies, and fare regulation protects them (Mizutani, 2004). It makes them have less incentive to minimise service inputs. Second, public firms are relatively new, and new technology saves operating costs (Mizutani, 2004). Third, private firms developed residential areas and leisure facilities near their rail service areas under the diversification strategy (Shoji, 2005). It created interdependency between rail and non-rail services. As much as rail operations internalise externalities from these property developments, the latter internalise externalities from rail operations. We believe that with this interdependency, private firms may have invested in improving their service quality — such as better customer service — for rail and non-rail activities. Doing so raises operating costs, and private firms may have lower cost efficiency[12] than public firms. Fourth, the government intervened in the market when private firms could not sustain losses. Quasi-public firms were established To preserve the unprofitable lines (Saito, 2015; Shoji, 2001). We believe that this intervention might have altered the behaviour of other private firm managers. Since they know there is a safety net whenever their firm cannot sustain losses, they become complacent and do not work as hard as expected. Fifth, quasi-public firms, which conducted unprofitable services, implemented cost-cutting measures to minimise losses. They “have found that demand is far less than projected” and are “doing everything in their power to improve their bottom lines” (Sekiguchi et al., 2010, p. 1286). Last, the network infrastructure is limited for competition since there can only be one train at one route stop at one time. While competition among lines and firms exists on

[12] which is a function of cost and output (car-km).

crucial intercity routes, the prevalence of such competition is limited (F. Mizutani, 1997). The urban rail operations in Tokyo are regarded as having a regional monopoly (Kato, 2016),

Policymakers must answer what they want to achieve from privatising and liberalising the urban rail market. Do they want to see better cost efficiency? According to the property rights theory of the firm, public firms should be less efficient and profitable than private ones (Boardman & Vining, 1989, p. 1). Vining and Boardman (1992) went on to demonstrate that ownership is both theoretically and empirically significant. Yet, we see some studies on rail services that show different results, such as Filippini and Maggi (1993), Lan and Lin (2003), and Canavan (2015). We have addressed the differences between these studies (i.e., different samples, different periods, and different types of efficiency[13]) that are believed to have caused differing results. Our findings suggested that private firms performed weaker than other firms in cost efficiency.

In this study, we have empirically demonstrated that better cost efficiency is not a definite outcome of having private urban rail firms. Private firms are profit-maximising entities, not necessarily cost-efficiency maximisers. We will explore and discuss the ownership effect on service effectiveness and cost effectiveness in the next chapter.

[13] Cost efficiency and technical efficiency.

Table 22. Trans-log Cost Function Regression Results (Model for Research Study 1)

```
Random-effects GLS regression                   Number of obs     =        552
Group variable: id                              Number of groups  =         46

R-sq:                                           Obs per group:
     within  = 0.7413                                         min =         12
     between = 0.9742                                         avg =       12.0
     overall = 0.9728                                         max =         12

                                                Wald chi2(17)     =    3493.55
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000
```

LnmcCELMpmcPM	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
LnmcQpN	.7490696	.056358	13.29	0.000	.63861	.8595292
LnmcQpN_DMM	-.2523734	.1056724	-2.39	0.017	-.4594874	-.0452593
LnmcQpN_DMU	-.290507	.0832885	-3.49	0.000	-.4537494	-.1272646
LnmcPEpmcPM	.1612759	.0217122	7.43	0.000	.1187208	.2038311
LnmcPLpmcPM	.4950746	.0255158	19.40	0.000	.4450645	.5450847
LnmcPMpmcPM	0	(omitted)				
LnmcN	.9430847	.0333984	28.24	0.000	.877625	1.008544
LnmcN_DMM	-.4184442	.1186433	-3.53	0.000	-.6509807	-.1859076
LnmcN_DMU	.0251065	.0570915	0.44	0.660	-.0867907	.1370037
LnmcQpNLnmcN	.1300572	.0354513	3.67	0.000	.0605739	.1995404
LnmcPEpmcPMLnmcPLpmcPM	.2360141	.0463818	5.09	0.000	.1451076	.3269207
LnmcPEpmcPMLnmcPMpmcPM	0	(omitted)				
LnmcPLpmcPMLnmcPMpmcPM	0	(omitted)				
halfLnmcPEpmcPM2	-.1945434	.050584	-3.85	0.000	-.2936861	-.0954007
halfLnmcPLpmcPM2	-.1243123	.0522893	-2.38	0.017	-.2267975	-.0218272
halfLnmcPMpmcPM2	0	(omitted)				
LnmcNLnmcPEpmcPM	-.0386899	.0123049	-3.14	0.002	-.062807	-.0145729
LnmcNLnmcPLpmcPM	.1233431	.0149579	8.25	0.000	.0940262	.15266
LnmcNLnmcPMpmcPM	0	(omitted)				
DMM	-.9584722	.2188037	-4.38	0.000	-1.38732	-.5296249
DMU	.1475098	.0758003	1.95	0.052	-.0010561	.2960757
Time	-.0064877	.0010459	-6.20	0.000	-.0085375	-.0044378
_cons	.0073412	.0434008	0.17	0.866	-.0777228	.0924053
sigma_u	.16828347					
sigma_e	.04938309					
rho	.92071368	(fraction of variance due to u_i)				

Note: Refer to Table 51 on page 230 for Regression Term Descriptions.

Table 23. Trans-log Cost Function Regression Results (Model for Research Study 2)

```
Random-effects GLS regression                   Number of obs     =        552
Group variable: id                              Number of groups  =         46

R-sq:                                           Obs per group:
     within  = 0.7454                                         min =         12
     between = 0.9736                                         avg =       12.0
     overall = 0.9723                                         max =         12

                                                Wald chi2(18)     =    3494.05
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000
```

LnmcCELMpmcPM	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
DOB	.3572549	.1439311	2.48	0.013	.0751551	.6393546
LnmcQpN	.754136	.0563978	13.37	0.000	.6435983	.8646737
LnmcQpN_DMM	-.3722932	.1160786	-3.21	0.001	-.5998031	-.1447833
LnmcQpN_DMU	-.3664888	.0886342	-4.13	0.000	-.5402086	-.192769
LnmcPEpmcPM	.1626403	.0215875	7.53	0.000	.1203296	.2049511
LnmcPLpmcPM	.4962735	.0253728	19.56	0.000	.4465437	.5460033
LnmcPMpmcPM	0	(omitted)				
LnmcN	.9119681	.0356205	25.60	0.000	.8421532	.9817829
LnmcN_DMM	-.4323876	.1184456	-3.65	0.000	-.6645367	-.2002385
LnmcN_DMU	.0237281	.0571792	0.41	0.678	-.0883411	.1357973
LnmcQpNLnmcN	.0898697	.039038	2.30	0.021	.0133566	.1663829
LnmcPEpmcPMLnmcPLpmcPM	.230124	.0461529	4.99	0.000	.1396661	.320582
LnmcPEpmcPMLnmcPMpmcPM	0	(omitted)				
LnmcPLpmcPMLnmcPMpmcPM	0	(omitted)				
halfLnmcPEpmcPM2	-.1904776	.0503014	-3.79	0.000	-.2890665	-.0918887
halfLnmcPLpmcPM2	-.1202947	.0519888	-2.31	0.021	-.2221908	-.0183986
halfLnmcPMpmcPM2	0	(omitted)				
LnmcNLnmcPEpmcPM	-.0385216	.0122303	-3.15	0.002	-.0624925	-.0145507
LnmcNLnmcPLpmcPM	.1216113	.0148871	8.17	0.000	.0924332	.1507894
LnmcNLnmcPMpmcPM	0	(omitted)				
DMM	-.7593095	.2331047	-3.26	0.001	-1.216186	-.3024326
DMU	.442213	.1418147	3.12	0.002	.1642613	.7201647
Time	-.0063016	.0010421	-6.05	0.000	-.0083441	-.004259
_cons	-.3433646	.1477262	-2.32	0.020	-.6329026	-.0538265
sigma_u	.17019503					
sigma_e	.04938309					
rho	.92234717	(fraction of variance due to u_i)				

Note: Refer to Table 51 on page 230 for Regression Term Descriptions.

Table 24. DEA-Tobit Regression Results for Cost Efficiency (CRS)

```
Random-effects tobit regression                 Number of obs     =        552
                                                   Uncensored     =        540
Limits: lower = -inf                               Left-censored  =          0
        upper = 0                                  Right-censored =         12

Group variable: id                              Number of groups  =         46
Random effects u_i ~ Gaussian                   Obs per group:
                                                              min =         12
                                                              avg =       12.0
                                                              max =         12

Integration method: mvaghermite                 Integration pts.  =         12

                                                Wald chi2(6)      =     482.69
Log likelihood  =  511.42984                    Prob > chi2       =     0.0000
```

LnIOCEc	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
DOB	-.5697635	.2478792	-2.30	0.022	-1.055598	-.0839291
LnTrafficDen	.4705514	.0614942	7.65	0.000	.350025	.5910778
LnN	.1852953	.0628368	2.95	0.003	.0621375	.3084531
DMM	-.1285073	.2419646	-0.53	0.595	-.6027492	.3457346
DMU	-.6766212	.2437205	-2.78	0.005	-1.154305	-.1989378
Time	.0171437	.0009627	17.81	0.000	.0152567	.0190306
_cons	-4.169647	.5620863	-7.42	0.000	-5.271315	-3.067978
/sigma_u	.3711093	.0538985	6.89	0.000	.2654702	.4767484
/sigma_e	.0736807	.0024251	30.38	0.000	.0689276	.0784338
rho	.9620761	.0112748			.9341575	.9794796

LR test of sigma_u=0: chibar2(01) = 1248.78   Prob >= chibar2 = 0.000

Table 25. DEA-Tobit Regression Results for Cost Efficiency (VRS)

```
Random-effects tobit regression                 Number of obs      =        552
                                                   Uncensored      =        476
Limits: lower = -inf                               Left-censored   =          0
        upper = 0                                  Right-censored  =         76

Group variable: id                              Number of groups   =         46
Random effects u_i ~ Gaussian                   Obs per group:
                                                             min =         12
                                                             avg =       12.0
                                                             max =         12

Integration method: mvaghermite                 Integration pts.   =         12

                                                Wald chi2(6)       =     158.08
Log likelihood  =  364.78784                    Prob > chi2        =     0.0000
```

LnIOCEv	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
DOB	-.2792163	.1721097	-1.62	0.105	-.6165451	.0581125
LnTrafficDen	.4526867	.0525966	8.61	0.000	.3495991	.5557742
LnN	.2385299	.0352573	6.77	0.000	.1694268	.3076329
DMM	.1693574	.200241	0.85	0.398	-.2231076	.5618225
DMU	-.552749	.1606873	-3.44	0.001	-.8676904	-.2378076
Time	.0050183	.001103	4.55	0.000	.0028565	.0071801
_cons	-4.090092	.3565292	-11.47	0.000	-4.788876	-3.391307
/sigma_u	.3875952	.0453371	8.55	0.000	.298736	.4764544
/sigma_e	.083779	.002861	29.28	0.000	.0781715	.0893865
rho	.9553643	.0104375			.9308317	.9723488

LR test of sigma_u=0: chibar2(01) = 1218.18   Prob >= chibar2 = 0.000

Table 26. DEA-Tobit Regression Results for Technical Efficiency (CRS)

```
Random-effects tobit regression                 Number of obs      =       552
                                                   Uncensored      =       508
Limits: lower = -inf                               Left-censored   =         0
        upper = 0                                  Right-censored  =        44

Group variable: id                              Number of groups   =        46
Random effects u_i ~ Gaussian                   Obs per group:
                                                              min =        12
                                                              avg =      12.0
                                                              max =        12

Integration method: mvaghermite                 Integration pts.   =        12

                                                Wald chi2(6)       =    241.13
Log likelihood  =  548.63452                    Prob > chi2        =    0.0000
```

LnIOTEc	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
DOB	-.6437194	.1545848	-4.16	0.000	-.9467001	-.3407388
LnTrafficDen	.5923135	.0489834	12.09	0.000	.4963078	.6883191
LnN	.1042905	.0438042	2.38	0.017	.0184359	.1901451
DMM	-.0877058	.1542836	-0.57	0.570	-.3900961	.2146845
DMU	-.4891544	.1387333	-3.53	0.000	-.7610666	-.2172423
Time	.0031825	.000831	3.83	0.000	.0015538	.0048113
_cons	-4.410947	.4236695	-10.41	0.000	-5.241323	-3.58057
/sigma_u	.3118699	.0394551	7.90	0.000	.2345394	.3892004
/sigma_e	.0626192	.0020995	29.83	0.000	.0585043	.0667341
rho	.9612472	.0099787			.9372956	.9771542

LR test of sigma_u=0: chibar2(01) = 1308.18   Prob >= chibar2 = 0.000

Table 27. DEA-Tobit Regression Results for Technical Efficiency (VRS)

```
Random-effects tobit regression                 Number of obs     =        552
                                                   Uncensored     =        401
Limits: lower = -inf                               Left-censored  =          0
        upper = 0                                  Right-censored =        151

Group variable: id                              Number of groups  =         46
Random effects u_i ~ Gaussian                   Obs per group:
                                                              min =         12
                                                              avg =       12.0
                                                              max =         12

Integration method: mvaghermite                 Integration pts.  =         12

                                                Wald chi2(6)      =     543.96
Log likelihood  =   360.2867                    Prob > chi2       =     0.0000
```

LnIOTEv	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
DOB	-.4816006	.1151809	-4.18	0.000	-.707351	-.2558501
LnTrafficDen	.6273311	.0376504	16.66	0.000	.5535377	.7011245
LnN	.2153935	.0230238	9.36	0.000	.1702677	.2605193
DMM	.1197971	.1293111	0.93	0.354	-.133648	.3732423
DMU	-.4093112	.1081488	-3.78	0.000	-.6212789	-.1973435
Time	-.0022195	.0009106	-2.44	0.015	-.0040042	-.0004347
_cons	-4.796026	.241155	-19.89	0.000	-5.268681	-4.323371
/sigma_u	.3665229	.0439735	8.34	0.000	.2803365	.4527094
/sigma_e	.0655052	.0024701	26.52	0.000	.0606638	.0703465
rho	.9690476	.007566			.9509978	.9812073

LR test of sigma_u=0: chibar2(01) = 1155.36   Prob >= chibar2 = 0.000

Chapter 7 Research Study 3: Exploring the Ownership and Other Effects on Cost Efficiency, Service Effectiveness, and Cost Effectiveness

7.1 Introduction

In Research Study 2 (Chapter 6), we found private firms less cost-efficient than other firms (i.e., quasi-public and public firms) in the Japanese urban rail sector. We explained some possible reasons for the finding. Yet, private firms are theoretically expected to be more service- and cost-effective than other firms (see Chapter 2: The Performance of Private Firms section). In this research study (Chapter 7), we are motivated to explore whether private firms in the Japanese urban rail sector have better service effectiveness and cost effectiveness than other firms (as depicted in Figure 18 on page 144).

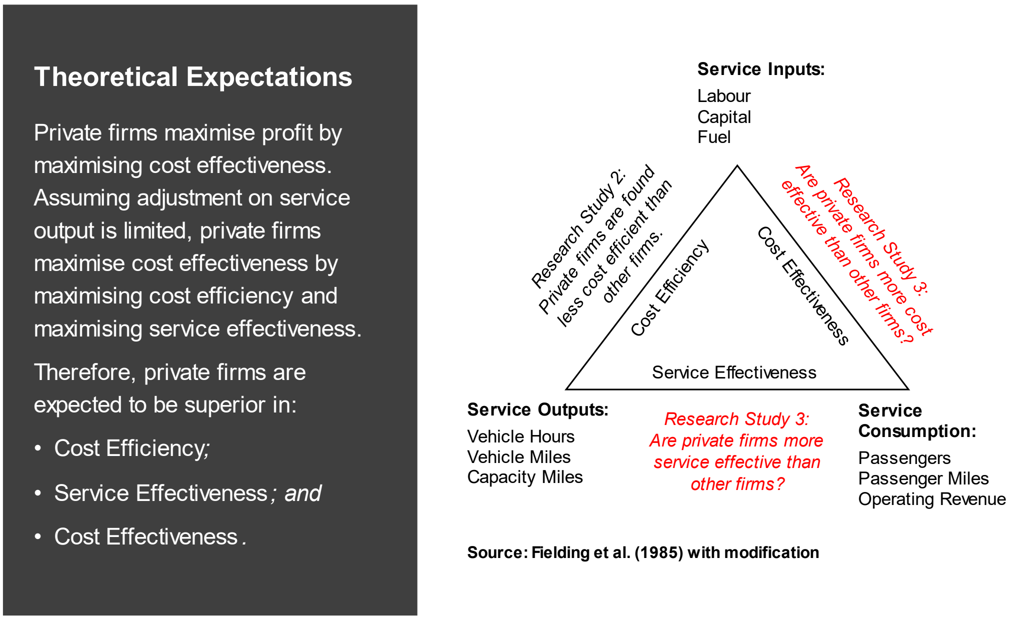

Figure 18. Theoretical Expectations on Private Firms' Performance (for Research Study 3)

In Chapter 2: Service effectiveness and Cost effectiveness sections, we highlighted several studies on private firms' service effectiveness and cost effectiveness in the land transport sector, such as Currie and De Gruyter (2016), Merkert et al. (2017) and Costa et al. (2021). Note that even though we have expanded our scope of literature from the rail sector to the land transport sector for cost efficiency, service effectiveness, and cost effectiveness, we found that the studies on private firms' service effectiveness and cost effectiveness are not as many as those on private firms' cost efficiency. However, we decided not to include the air and maritime transport sectors because of their market uniqueness.

We also highlighted authors that used the term 'efficiency' in their studies but measured the relationship between service inputs and service consumption, which equals cost effectiveness. One example is Costa et al. (2021). If there is a difference in how a factor affects cost efficiency and cost effectiveness, using these terms inaccurately may give a partial picture of the overall performance. Henceforth, we are further motivated to evaluate and compare how ownership, traffic density, scale, mode, time, and population density[1] affect cost efficiency[2], service effectiveness, and cost effectiveness.

We decided to adopt one method in this study: the DEA-Tobit regression. We utilised the results from Research Study 2 (Chapter 6) for private firms' cost efficiency. We first conducted DEA to produce the relevant scores for private firms' service effectiveness and cost effectiveness. We set the following specifications when running DEA:

Type of score	*Input for DEA*	*Output for DEA*
Service effectiveness	Q (thousand car-km)	Y (thousand passenger-km)
Cost effectiveness	C_{ELM} (Yen)	Y (thousand passenger-km)

We used VRS scores since the scale is prevalent in the rail industry (Lan & Lin, 2003; Merkert et al., 2017; Tsai et al., 2015).

[1] For service effectiveness and cost effectiveness since these performance dimensions involve a demand related measure (i.e., service consumption).

[2] Private firms' performance in cost efficiency from Research Study 2 is used to compare and evaluate against service effectiveness and cost effectiveness.

We used output orientation for service effectiveness scores since we assumed firms are expected to provide reliable routine services, limiting their service output[3] (car-km) adjustment. Service output denotes supply availability to consumers, and in local transport, providing service output is considered a service obligation (Cowie, 1999; Walter, 2011). We applied input orientation for cost effectiveness scores since demand-related factors partly influence service consumption, and firms have more control over service input (Fitzová et al., 2018).

After obtaining DEA cost efficiency scores and DEA technical-efficiency scores, we performed Tobit regression. We specified the effectiveness scores (i.e., service effectiveness in one regression and cost effectiveness in another) as the dependent variable. We then selected D_t (car-km/operating-km), N (operating-km), DM_{MR} (dummy for monorail), DM_{UG} (dummy for under-ground), DO_B (dummy for private firms), PD (population density), and T (year) as the independent variables. We included DO_B to determine whether private firms are more service-effective or cost-effective than other firms. We included D_t, N, DM_{MR}, *and* DM_{UG} to evaluate how traffic density, scale, and mode affect cost efficiency (measured in Research Study 2), service effectiveness, and cost effectiveness. Doing so will help us understand more about these performance dimensions' differences. We included PD since population density positively influences service consumption (Ingvardson & Nielsen, 2018; Lobo & Couto, 2016).

Note that the network DEA method is different from the standard DEA method. In addition to the absence of convexity constraint in the network DEA method, this method is relatively new and still undergoing development. We prefer to utilise the standard DEA method, which has been established in the literature.

[3] Service output (car-km) is used as the input for DEA in calculating service effectiveness.

7.2 Objectives

We aimed to explore further the ownership effect on each performance dimension (i.e., cost efficiency, service effectiveness, and cost effectiveness) in the Japanese urban rail sector and investigate the density, scale, and mode effects on each performance dimension. In doing so, we set the following objectives:

a. determine whether private firms are more service effective than other firms,
b. determine whether private firms are more cost-effective than other firms,
c. compare and evaluate private firms' performance in cost efficiency, service effectiveness, and cost effectiveness, and
d. compare and evaluate how density, scale, and mode affect cost efficiency, service effectiveness, and cost effectiveness.

In this study, private firms' cost efficiency from Research Study 2 is used to compare and evaluate private firms' service effectiveness and cost effectiveness.

7.3 Results and Discussion

This section is divided into two subsections. The first subsection compares the regression results for all performance dimensions: cost efficiency, service effectiveness, and cost effectiveness. The purpose is to evaluate whether there is any difference between the results. Karlaftis and Tsamboulas (2012) found that the performance of a system in one dimension (such as efficiency) is not indicative of how well it will perform in another dimension (such as effectiveness). We will inspect how ownership, traffic density, scale, mode, time, and population density affect:

a. cost efficiency,
b. service effectiveness, and
c. cost effectiveness.

Cost efficiency refers to the relationship between service input and service output. Service effectiveness refers to the relationship between service output and service consumption. Cost effectiveness refers to the relationship between service input and service consumption. We employed regression equations in this study. Because our regression equation is in the natural log, holding all other variables constant and exponentiating the equation will yield the relevant ratio variables. The second subsection focuses on the Japanese private urban rail firms' performance in cost efficiency, service effectiveness, and cost effectiveness.

7.3.1 Results Comparison

We compared the DEA-Tobit regression results for all performance dimensions: cost efficiency[4], service effectiveness, and cost effectiveness. We are interested in six effects: ownership, traffic density, scale, mode, time, and population density effects. Population density is a new variable compared to the previous chapters. We included this variable since population density positively influences service consumption (Ingvardson & Nielsen, 2018; Lobo & Couto, 2016). The definitions of these variables are stated in Chapter 2: Data and Variables section. More information is provided in Chapter 3: Methodology. When discussing, we referred to excerpts from the relevant regression results. For more detailed results, please refer to:

- Table 34. DEA-Tobit Regression Results for Cost efficiency (VRS) on page 163,
- Table 35. DEA-Tobit Regression Results for Service effectiveness (VRS) on page 164, and
- Table 36. DEA-Tobit Regression Results for Cost effectiveness (VRS) on page 165.

We observed that different factors affect performance dimensions differently — except for population density. Ownership, traffic density,

[4] For private firms' cost efficiency, we utilised the results from Research Study 2 (Chapter 6).

scale, mode, and time affect cost efficiency, service effectiveness, and cost effectiveness differently.

7.3.1.1 Ownership Effect

Table 28 on page 149 presents the ownership effect on cost efficiency, service effectiveness, and cost effectiveness. The results show that ownership affects all performance dimensions. At 11% significance level, private firms are 24.4% less cost-efficient than other firms. At 1% significance level, private firms are 117% more service effective than other firms. At 20% significance level, private firms are 25.7% more cost-effective than other firms.

Table 28. Ownership Effect on Different Performance Dimensions

Factor of interest			**Performance Dimension**		
			Cost efficiency	**Service effectiveness**	**Cost effectiveness**
Ownership Effect[5]	Private vs Others	Diff.	(0.244)	1.170	0.257
		Sig.	0.105	0.000	0.194

Note: Brackets represent a negative value. Other firms consist of public and quasi-public firms.

We further observed that ownership affects different performance dimensions in different ways. While private ownership negatively affects cost efficiency (24.4% less cost-efficient than others), it positively affects service effectiveness (117% more service effective than others) and cost effectiveness (25.7% more cost-effective than others). The results indicate that private firms perform differently in cost efficiency, service effectiveness, and cost effectiveness.

[5] Ownership effect is derived by $x = e^{(\beta_{DO})} - 1$. Multiplying x by 100, the interpretation will be “private firms is *x* percent more cost efficient/service effective/cost effective than other firms (omitted variable)”. Brackets represent a negative value. In this case, the interpretation will be “private firms are *x* percent less cost efficient/service effective/cost effective than other firms”.

Although private firms are less cost-efficient than other firms, they are more service-effective and cost-effective than the latter. It may indicate that private firms prioritise profit maximisation. In doing so, they seek high service consumption, yielding high service effectiveness. Private firms do not mind incurring higher operating costs as long as they gain enough additional service consumption that could maximise their profit. For instance, they would spend more on improving service quality to gain ridership. As a result, their cost efficiency[6] may be compromised. We will discuss private firms' performance more in the discussion section in para 7.3.2 on page 158.

7.3.1.2 Traffic Density Effect

Table 29 on page 150 presents the traffic density effect on cost efficiency, service effectiveness, and cost effectiveness. The results show that traffic density significantly affects cost efficiency and service effectiveness, but not so pertaining to cost effectiveness. At 1% significance level, cost efficiency will increase by 0.453% given a percentage increase in traffic density. At 1% significance level, service effectiveness will decrease by 0.332% given a percentage increase in traffic density. At 66% significance level, cost effectiveness will reduce by 0.026%, given a percentage increase in traffic density.

Table 29. Traffic Density Effect on Different Performance Dimensions

Factor of interest		**Performance Dimension**		
		Cost efficiency	**Service effectiveness**	**Cost effectiveness**
Traffic Density Effect	Coef.	0.453	(0.332)	(0.026)
	Sig.	0.000	0.000	0.654

Note: Brackets represent a negative value.

[6] which is a relation between service input (like operating costs) and service output (like car-km).

It can be said that traffic density affects different performance dimensions in different ways. Even though a higher traffic density may likely result in better cost efficiency, it may likely lead to lower service effectiveness and may unlikely improve cost effectiveness. The results indicate that traffic density affects cost efficiency, service effectiveness, and cost effectiveness differently.

Although it increases cost efficiency, a higher traffic density will unlikely generate enough additional service consumption[7]. It is indicated by the negative coefficient on service effectiveness and an insignificant coefficient on cost effectiveness. Increasing traffic density on the existing track will unlikely improve cost effectiveness (specifically, service consumption). In this situation, if a firm aims for profit maximisation (which includes maximising service consumption), it will not increase the traffic density unless it needs to meet the expected minimum service levels.

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[7] There might be an increase in service consumption, but the increase is not enough to maintain or improve service effectiveness and cost effectiveness.

7.3.1.3 Scale Effect

Table 30 on page 152 presents the scale effect on cost efficiency, service effectiveness, and cost effectiveness. At 1% significance level, cost efficiency will increase by 0.239% given a percentage increase in scale. At 8% significance level, service effectiveness will decrease by 0.143% given a percentage increase in scale. At 15% significance level, cost effectiveness will reduce by 0.056% given a percentage increase in scale.

Table 30. Scale Effect on Different Performance Dimensions

Factor of interest		**Performance Dimension**		
		Cost efficiency	**Service effectiveness**	**Cost effectiveness**
Scale Effect	Coef.	0.239	(0.143)	(0.056)
	Sig.	0.000	0.071	0.142

Note: Brackets represent a negative value.

The results show that scale affects cost efficiency and service effectiveness with very strong confidence levels (at least 92%) and affects cost effectiveness with a slightly lower confidence level (85%). It can be said that scale affects different performance dimensions in different ways. Even though a more extensive scale may likely result in better cost efficiency, it may lead to lower service effectiveness and decreased cost effectiveness. The results indicate that scale affects cost efficiency, service effectiveness, and cost effectiveness differently.

Although it increases cost efficiency, a larger scale will unlikely generate enough additional service consumption[8]. The negative coefficients on service effectiveness and cost effectiveness indicate this. Indeed, the increasing scale will likely decrease cost

[8] There might be an increase in service consumption, but the increase is not enough to maintain or improve service effectiveness and cost effectiveness.

effectiveness. Based on the results, we anticipate that private firms (which aim for profit maximisation) do not have any tendency to increase their scale or expand their network size.

7.3.1.4 Mode Effect

Table 31 on page 154 presents the mode effect on cost efficiency, service effectiveness, and cost effectiveness. It can be seen that:

- at 40% significance level, the monorail is 18.5% more cost-efficient than over-ground,
- at 93% significance level, the monorail is 2% more service effective than over-ground,
- at 88% significance level, the monorail is 2.7% less cost-effective than over-ground,
- at 1% significance level, under-ground is 42.5% less cost-efficient than over-ground,
- at 1% significance level, under-ground is 80.2% more service effective than over-ground,
- at 37% significance level, under-ground is 15% less cost-effective than over-ground,
- at 1% significance level, under-ground is 51.4% less cost-efficient than monorail,
- at 2% significance level, under-ground is 76.7% more service-effective than monorail, and
- at 31% significance level, under-ground is 12.6% less cost-effective than the monorail.

Table 31. Mode Effect on Different Performance Dimensions

Factor of interest			Performance Dimension		
			Cost efficiency	**Service effectiveness**	**Cost effectiveness**
Mode Effect[9]	M vs O	Diff.	0.185	0.020	(0.027)
		Sig.	0.398	0.929	0.874
	U vs O	Diff.	(0.425)	0.802	(0.150)
		Sig.	0.001	0.008	0.360
	U vs M	Diff.	(0.514)	0.767	(0.126)
		Sig.	0.000	0.012	0.303

Note: Brackets represent a negative value.

The results show that mode affects cost efficiency, service effectiveness, and cost effectiveness to some extent. There are significant differences in cost efficiency and service effectiveness between rail modes (at least 98% confidence level) — except between monorail and over-ground. There are also differences in cost effectiveness between rail modes, although with a much lower confidence level (at least 63%) — except between monorail and over-ground. The difference between monorail and over-ground is not substantial in cost efficiency (60% confidence level) and negligible in service effectiveness (7% confidence level) and cost effectiveness (12% confidence level).

Mode variable affects different performance dimensions in different ways. The difference between under-ground and other rail modes in

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[9] Mode effect (or mode difference) is derived by $x = e^{(\beta_{DM})} - 1$. Multiplying *x* by 100, the interpretation will be "Mode A is *x* percent more cost efficient/service effective/cost effective than over-ground (omitted variable)". Brackets represent a negative value. In this case, the interpretation will be "Mode A is *x* percent less cost efficient/service effective/cost effective than over-ground". Mode difference between under-ground and monorail is derived by $x = e^{\left(\beta_{DM_U} - \beta_{DM_M}\right)} - 1$.

every performance dimension is relatively significant (ranging from 63% to 99% confidence levels). However, monorail and over-ground differences in every performance dimension are relatively insignificant (ranging from 7% to 60% confidence levels). Under-ground has the weakest cost efficiency and cost effectiveness despite having the most substantial service effectiveness. The results indicate that, to some extent, the mode variable has a different effect on cost efficiency, service effectiveness, and cost effectiveness.

Mode differences are significant between under-ground and over-ground, and between under-ground and monorail. The differences are significant in cost efficiency and service effectiveness but weak in cost effectiveness. However, they are generally insignificant between the monorail and over-ground across all performance dimensions.

Under-ground has the weakest cost efficiency but the most substantial service effectiveness. The strength offsets the weakness, making under-ground's cost effectiveness performance not far below the other modes. We believe that different technological characteristics such as train size, capacity and length may require additional maintenance amounts but simultaneously offer different levels of benefit.

The importance of our findings on mode effect in this chapter is twofold. Firstly, they reaffirm that mode is an important variable to consider when evaluating the performance of urban rail services. Research Study 1 (Chapter 5) found that the mode effect is significant in cost efficiency. In this chapter, we discovered that the mode variable significantly affects service effectiveness. Secondly, they suggest that cost efficiency, service effectiveness, and cost effectiveness are different performance measurements and are not interchangeable. Therefore, one should know which to measure when conducting a performance study on urban rail services. Our findings support what Perry et al. (1988) stated, that using different analyses could lead to varying outcomes.

7.3.1.5 Time Effect

Table 32 on page 156 presents the time effect on cost efficiency, service effectiveness, and cost effectiveness. It can be seen that at 1% significance level,

- cost efficiency will increase by 0.005% from one year to another,
- service effectiveness will decrease by 0.007% from one year to another, and
- cost effectiveness will reduce by 0.006% from one year to another.

Table 32. Time Effect on Different Performance Dimensions

Factor of interest		**Performance Dimension**		
		Cost efficiency	**Service effectiveness**	**Cost effectiveness**
Time	Coef.	0.005	(0.007)	(0.006)
	Sig.	0.000	0.000	0.000

Note: Brackets represent a negative value.

The results show that time significantly affects all performance dimensions (with 99% confidence level). However, time affects different performance dimensions in different ways. While time positively affects cost efficiency, it negatively affects service effectiveness and cost effectiveness. The results indicate that time affects cost efficiency, service effectiveness, and cost effectiveness differently.

The improvement in cost efficiency with time may suggest that urban rail firms experience productivity improvements. Despite that, they face difficulty in generating enough additional service consumption[10]. The negative coefficients on service effectiveness and cost

[10] There might be an increase in service consumption, but the increase is not enough to maintain or improve service effectiveness and cost effectiveness.

effectiveness indicate this. According to Jitsuzumi and Nakamura (2010), modal shifts and an ageing population have negatively affected service consumption.

7.3.1.6 Population Density Effect

Table 33 on page 157 presents the population density effect on service effectiveness and cost effectiveness. At 1% significance level, service effectiveness will increase by 0.192% given a percentage increase in population density. At 4% significance level, cost effectiveness will increase by 0.081% given a percentage increase in population density.

Table 33. Population Density Effect on Different Performance Dimensions

Factor of interest		**Performance Dimension**	
		Service effectiveness	Cost effectiveness
Population Density	Coef.	0.192	0.081
	Sig.	0.009	0.039

The results show that population density significantly affects these performance dimensions (at least 96% confidence level). A higher population density may highly likely result in better service effectiveness and cost effectiveness. The results are consistent in showing that population density improves service effectiveness and cost effectiveness. They are in tandem with Lobo and Couto (2016) and Ingvardson and Nielsen (2018), who found that population density positively influenced service consumption, a component of service effectiveness and cost effectiveness.

A positive effect of population density on service effectiveness and cost effectiveness suggests that people prefer urban rail services as an area becomes more densely populated. In a densely populated area, using urban rails offers more convenience than using private vehicles concerning time and cost since private vehicles are subject to traffic congestion and limited parking availability, which can be very expensive.

7.3.2 Discussion

All in all, we observed that the effect of one factor is different in every performance dimension. This finding is consistent with Karlaftis and Tsamboulas (2012), who found that the performance of a system in one dimension is not indicative of its performance in the other dimension, and Kerstens (1996), who noted that the performance of transit systems varies significantly depending on the output specification used. We opine that assessing all the performance dimensions — and subsequently interpreting their results with each other — offers a comprehensive understanding of urban rail performance.

Research Study 2 (Chapter 6) found that private firms are 24.4% less cost-efficient than other firms — with an 89% confidence level. In this research study (Chapter 7), private firms are 117% more service effective and 25.7% more cost-effective than other firms — with 99% and 80% confidence levels, respectively. Although the Japanese private urban rail firms do not perform as theoretically expected in cost efficiency, they perform so in service effectiveness and cost effectiveness.

One possible reason the Japanese private urban rail firms are more service-effective is their business diversification strategy. Under this strategy, private firms develop residential areas and leisure facilities near their rail service areas (Shoji, 2005). With the interdependency between these property developments and rail operations, we believe private firms may have provided better service quality — such as better customer service — for rail and non-rail activities. In doing so, they strengthened and stabilised their urban rail service consumption, producing better service effectiveness than other firms.

Another possible reason for the Japanese private urban rail firms being more service effective is that other firms, especially quasi-public firms, may run their services at the minimum expected service level, albeit at low service consumption. Sekiguchi et al. (2010, p. 1286) stated that many of these firms "have found that demand is far less than projected". These urban rail operations are not attractive to private firms. Indeed, some of these unattractive urban rail operations are inherited from private firms. Quasi-public firms were established to preserve the operation of these services (Saito, 2015; Shoji, 2001).

One reason for the Japanese private urban rail firms being more cost-effective was offered by Mizutani (1994). In many ways, private firms are superior. They travelled faster, charged lower fares, experienced higher labour productivity, and benefited from a lower average employee wage compared to other firms, all while requiring fewer subsidies.

Perhaps the most compelling reason the Japanese private urban rail firms are more cost-effective is that they are profit-maximising entities. They are better positioned than other firms in profitability. It might be why our finding on the Japanese private urban rail firms' cost effectiveness performance is very much similar to that of Mizutani (1994), even though our studies are more than a decade apart.

As theoretically explained in Literature Review: The Performance of Private Firms section (Chapter 2), private owners' goal of gaining benefits[11] from their investment puts firm managers under constant pressure to perform well. Private owners may change the firm's management if poor performance affects profitability. Hence, private firms will strive to maximise profit in such an environment. Japan's Railway Accounting Regulations, which clearly distinguish between rail lines and non-rail businesses in financial reporting, might have helped private owners to monitor their firm's profit performance. Prioritising social welfare, other firms might not have strived as hard as private firms to maximise profit. Canavan (2015) addressed the contrasts between private and public incentives when he discovered private firms are less efficient than public firms in his worldwide

[11] Such as dividends and higher share prices.

efficiency study on 27 metros from 2004 to 2012. Private metros may be more prone to forgo services in order to increase profits.

The principal-agent problem, which is less severe in the private firms' environment, might have also helped the Japanese private urban rail firms to be more cost-effective than other firms (quasi-public and public).

7.4 Conclusion

We concluded that this study has met its aims and objectives. It has offered a deeper understanding of how ownership affects service effectiveness and cost effectiveness in the Japanese urban rail sector. It has also provided a greater comprehension of how ownership, density, scale, and mode affect cost efficiency, service effectiveness, and cost effectiveness.

Research Study 2 (Chapter 6) indicated that private firms exhibit weaker cost efficiency than other firms. In this research study, however, our findings suggested that private firms demonstrate superior service effectiveness and cost effectiveness compared to their counterparts. Although private urban rail firms in Japan do not perform as well as theoretically expected in terms of cost efficiency (refer to Research Study 2 in Chapter 6), they performed as expected regarding service effectiveness and cost effectiveness.

Private firms' superior performance in service effectiveness may be attributed to their business diversification strategy. This approach has strengthened and stabilised their urban rail service consumption, leading to better service effectiveness than other firms. An additional factor contributing to the superior service effectiveness of Japanese private urban rail firms may be the tendency of other firms, particularly quasi-public entities, to operate their services at the bare minimum level of expected service, despite low service consumption. According to Sekiguchi et al. (2010, p. 1286), it has been observed that a significant number of these firms have encountered a situation where the demand for services is considerably lower than what was initially anticipated.

Mizutani (1994) explained the greater cost effectiveness of Japanese private urban rail firms. Private firms exhibited superior performance in various aspects, such as faster travel, lower fares, higher labour productivity, and lower average employee wage than their counterparts.

One persuasive argument in favour of the private urban rail firms in Japan being more cost-effective is the fact that these firms are profit-maximising entities. It may explain why our findings regarding the cost effectiveness performance of Japanese private urban rail firms are so similar to those of Mizutani (1994) despite our studies being conducted more than a decade apart. As we have theorised in the Literature Review: The Performance of Private Firms section (Chapter 2), the goal of private owners to obtain a return on their investment places constant pressure on firm managers to perform well. The Railway Accounting Regulations of Japan, which differentiate between rail lines and non-rail businesses in financial reporting, could have assisted private owners in monitoring the profit performance of their firms. Moreover, quasi-public and public firms that place a high value on social welfare might not have exerted the same effort as private firms in pursuing profit maximisation. Canavan (2015) observed that private firms demonstrated inferior efficiency levels compared to their public counterparts. He mentioned that private metro systems may exhibit a higher inclination towards prioritising the maximisation of profits as opposed to the provision of services.

The principal-agent problem, which is comparatively less pronounced in the private sector, may have also contributed to the superior cost effectiveness of Japanese private urban rail firms compared to quasi-public and public firms.

We found that different factors, except for population density, affect performance dimensions differently. Ownership, traffic density, scale, mode, and time influence cost efficiency, service effectiveness, and cost effectiveness in different ways. These findings align with the research conducted by Karlaftis and Tsamboulas (2012), which similarly concluded that the performance of a system in a particular aspect, such as cost efficiency, does not necessarily reflect its performance in another aspect, such as service effectiveness. These findings also agree with Kerstens (1996), who found that the performance of public transportation systems varied significantly depending on the output specification used. We believe that a thorough understanding of urban rail performance can be attained by first evaluating all of the performance dimensions and then interpreting the findings with each other.

Table 34. DEA-Tobit Regression Results for Cost efficiency (VRS)

```
Random-effects tobit regression                 Number of obs     =        552
                                                   Uncensored     =        476
Limits: lower = -inf                               Left-censored  =          0
        upper = 0                                  Right-censored =         76

Group variable: id                              Number of groups  =         46
Random effects u_i ~ Gaussian                   Obs per group:
                                                              min =         12
                                                              avg =       12.0
                                                              max =         12

Integration method: mvaghermite                 Integration pts.  =         12

                                                Wald chi2(6)      =     158.08
Log likelihood  =  364.78784                    Prob > chi2       =     0.0000
```

LnIOCEv	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
DOB	-.2792163	.1721097	-1.62	0.105	-.6165451	.0581125
LnTrafficDen	.4526867	.0525966	8.61	0.000	.3495991	.5557742
LnN	.2385299	.0352573	6.77	0.000	.1694268	.3076329
DMM	.1693574	.200241	0.85	0.398	-.2231076	.5618225
DMU	-.552749	.1606873	-3.44	0.001	-.8676904	-.2378076
Time	.0050183	.001103	4.55	0.000	.0028565	.0071801
_cons	-4.090092	.3565292	-11.47	0.000	-4.788876	-3.391307
/sigma_u	.3875952	.0453371	8.55	0.000	.298736	.4764544
/sigma_e	.083779	.002861	29.28	0.000	.0781715	.0893865
rho	.9553643	.0104375			.9308317	.9723488

LR test of sigma_u=0: chibar2(01) = 1218.18   Prob >= chibar2 = 0.000

Table 35. DEA-Tobit Regression Results for Service effectiveness (VRS)

```
Random-effects tobit regression                 Number of obs     =        552
                                                   Uncensored     =        515
Limits: lower = -inf                               Left-censored  =          0
        upper = 0                                  Right-censored =         37

Group variable: id                              Number of groups  =         46
Random effects u_i ~ Gaussian                   Obs per group:
                                                              min =         12
                                                              avg =       12.0
                                                              max =         12

Integration method: mvaghermite                 Integration pts.  =         12

                                                Wald chi2(7)      =      75.20
Log likelihood  =  331.04252                    Prob > chi2       =     0.0000
```

LnOOSFXv	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
DOB	.7747114	.2087903	3.71	0.000	.3654898	1.183933
LnTrafficDen	-.331525	.0818838	-4.05	0.000	-.4920143	-.1710356
LnN	-.1427295	.0791374	-1.80	0.071	-.2978359	.0123769
DMM	.019414	.2172013	0.09	0.929	-.4062927	.4451206
DMU	.5886295	.2211631	2.66	0.008	.1551578	1.022101
Time	-.0072088	.0013186	-5.47	0.000	-.0097933	-.0046243
LnPopDen_SP	.191516	.0729122	2.63	0.009	.0486107	.3344212
_cons	.0754957	.6833331	0.11	0.912	-1.263812	1.414804
/sigma_u	.4831424	.0692013	6.98	0.000	.3475104	.6187744
/sigma_e	.0994571	.0033266	29.90	0.000	.0929371	.1059771
rho	.9593466	.0118395			.9302147	.977727

LR test of sigma_u=0: chibar2(01) = 1223.27   Prob >= chibar2 = 0.000

Table 36. DEA-Tobit Regression Results for Cost effectiveness (VRS)

```
Random-effects tobit regression                 Number of obs      =        552
                                                   Uncensored      =        509
Limits: lower = -inf                               Left-censored   =          0
        upper = 0                                  Right-censored =         43

Group variable: id                              Number of groups   =         46
Random effects u_i ~ Gaussian                   Obs per group:
                                                              min =         12
                                                              avg =       12.0
                                                              max =         12

Integration method: mvaghermite                 Integration pts.   =         12

                                                Wald chi2(7)       =      50.71
Log likelihood  =  370.53005                    Prob > chi2        =     0.0000
```

LnIOCFXv	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
DOB	.2283842	.1756703	1.30	0.194	-.1159233	.5726918
LnTrafficDen	-.0263114	.0586132	-0.45	0.654	-.1411911	.0885683
LnN	-.0562397	.0382659	-1.47	0.142	-.1312394	.01876
DMM	-.0278647	.1750282	-0.16	0.874	-.3709138	.3151843
DMU	-.1623504	.1774332	-0.91	0.360	-.5101132	.1854124
Time	-.0055342	.001202	-4.60	0.000	-.0078901	-.0031784
LnPopDen_SP	.0805119	.0389653	2.07	0.039	.0041413	.1568825
_cons	-.7458221	.4438925	-1.68	0.093	-1.615835	.1241913
/sigma_u	.253438	.0279735	9.06	0.000	.198611	.308265
/sigma_e	.0933775	.0030574	30.54	0.000	.0873852	.0993699
rho	.8804751	.0241185			.8264922	.9213685

LR test of sigma_u=0: chibar2(01) = 918.02   Prob >= chibar2 = 0.000

Chapter 8 Conclusion

In Chapter 2, we reviewed the previous studies on the performance of urban rail modes and the performance of private firms in the land transport sector[1]. In addition, we discussed the benefits of understanding the cost structure and touched on the theoretical assumptions for the performance of private firms. We discovered gaps along the way, which prompted us to perform three research studies. This chapter is divided into five sections. The first three sections conclude the findings from the three research studies. The fourth section emphasises main research contributions. The final section discusses research limitations and suggests areas for future research.

8.1 Research Study 1

In Research Study 1 (Chapter 5), we aimed to understand the cost structure of each urban rail mode in Japan and determine whether there is any significant difference between them. To achieve these research aims, we set the following research objectives:

a. to determine whether operating costs vary between modes and whether there is a significant difference between them,
b. to determine whether economies of density characteristics vary between modes and whether there is a significant difference between them, and
c. to determine whether economies of scale characteristics vary between modes and whether there is a significant difference between them.

We concluded that the study's aims and objectives were met. It has given us a better grasp of the costs associated with over-ground,

[1] We expanded our scope of literature from rail sector to land transport sector since we found the studies on private firms' cost efficiency, service effectiveness and cost effectiveness were limited. However, we decided not to include air and maritime transport sectors because of their market uniqueness.

monorail, and under-ground rail modes in Japan and how they differ. This study has shown significant differences in operational costs across the different modes. Our findings in the study also imply several ways in which economies of density and scale vary amongst urban train systems. These findings contribute to the current literature, in which studies such as Keeler (1974), Savage (1997), Mizutani (2004), Graham (2008) and Brage-Ardao et al. (2015) discovered that rail services (including urban railways) exhibit growing RTD but steady RTS. To be more exact, we found that over-ground, monorail, and under-ground all have their rates of RTD growth, even though there is no significant distinction between the monorail and under-ground. We also determined that monorail has increasing RTS, whereas over-ground and under-ground rail have constant RTS. Furthermore, we discovered that the operating costs differ for each urban rail mode depending on the traffic density and network length.

While doing the analyses in Research Study 1, we discovered that the results obtained using an econometric tool were different from those obtained using simple ratio statistics, leading us to conclude that the results obtained using an econometric tool are more accurate.

Our findings on the differences among urban rail modes align with those of Savage (1997), who looked at the operating costs of urban rail modes in the United States of America. Given the findings of Graham (2008), Ingvardson and Nielsen (2018), Min et al. (2017), and Tsai et al. (2015), which all discovered that urban rail modes differed in terms of production, we suggest addressing and recognising mode difference in future urban rail research.

Several policy implications have been identified. First, there is a possibility to incorporate the anticipated operating costs into the cost-benefit analysis alongside the infrastructure costs, the expected level of demand, and any other pertinent information. This incorporation will facilitate making more informed decisions about which rail mode to build. Second, transit authorities and businesses can use our model and its results as a resource for estimating future costs. Third, our research gives Japan's authorities a comprehensive picture of how the ceiling price could vary amongst urban rail modes while accounting for the full cost level of the relevant operator. Fourth, given that the cost function is used in Japan's yardstick competition, the mode effect might be incorporated into the model to produce more accurate results. Five, our approach can help determine how to organise franchises if a competitive tendering approach is utilised, as it will show the ideal size of the franchise.

We think that when decision-makers, regulators, and stakeholders have a more precise grasp of the cost structures of urban rail modes, they will be better able to decide on policies, regulations, and future investments relevant to urban rail services. We believe that more cooperation between regulators and industry players will be directed towards finding and acquiring the necessary data in regions where cost function studies are rare, particularly in the urban rail sector.

We recommend replicating this empirical research in other regions where sufficient data is available for a more conclusive comprehension of the cost differences between urban rail modes. It would be interesting to see if the results are the same. Furthermore, we hope that future empirical research will clarify the RTD and RTS of urban rail modes. We anticipate that the disparities in regional definitions of urban rail mode will make synthesising the current and future empirical findings difficult.

8.2 Research Study 2

Research Study 2 (Chapter 6) explored the ownership effect on cost efficiency in the Japanese urban rail sector. To achieve these research aims, we set the following research objectives:

a. to determine whether adding the ownership variable into Research Study 1's trans-log cost function model does not materially change the coefficients elsewhere,

b. to explore whether different methods (i.e., trans-log cost function and DEA-Tobit regression) would yield similar results, and
c. to determine whether private firms are more cost-efficient than other firms.

The study has successfully achieved its intended aims and objectives. The findings from Research Study 1 were reaffirmed by the consistent results of incorporating the ownership effect into the trans-log cost function model utilised in the preceding chapter (Research Study 1). Also, it was observed that outcomes obtained from the trans-log cost function, the DEA-Tobit Cost Efficiency, and the DEA-Tobit Technical Efficiency models exhibit resemblance, albeit not identical. This study compared the results from four DEA-Tobit regression models against those of the trans-log cost function model. These models are DEA-Tobit Cost Efficiency CRS, DEA-Tobit Cost Efficiency VRS, DEA-Tobit Technical Efficiency CRS, and DEA-Tobit Technical Efficiency VRS. It was found that the DEA-Tobit Cost Efficiency VRS model yielded results that were most comparable to those of the trans-log cost function model. This outcome is anticipated, given that the trans-log cost function is also conducive to VRS.

This research study has also provided us with an enhanced understanding of the impact of ownership on cost efficiency within the urban rail industry in Japan. This study suggests that private firms exhibited low cost, cost efficiency, and technical efficiency compared to other firms while controlling for other variables at the sample mean. It is also established that this assertion remains valid when using two commonly employed approaches for determining efficiency: the trans-log cost function and the DEA-Tobit regression.

Our finding on private firms' cost efficiency is counterintuitive considering Chapter 2's theoretical rationale, which anticipates superior performance from private firms. This finding could be due to several different factors. First, according to Mizutani (2004), smaller private firms often function as regional monopolies, and their protection is ensured through fare regulation. Therefore, they will have fewer reasons to try and cut costs. Second, public firms are relatively new; new technology reduces operating costs (Mizutani, 2004). Three, as part of the diversification strategy, private firms build residential neighbourhoods and recreational amenities close to the areas where they provide rail service (Shoji, 2005). Because of this, rail services and other types of services became interdependent on one another. Rail operations and property developments mutually internalise externalities, with the former absorbing externalities from the latter and the latter absorbing externalities from the former. We believe that because of this interdependency, private firms may have invested in increasing the quality of their services by providing better customer service. It raises operating costs; therefore, we may find that private firms have weaker cost efficiency than public firms. Fourth, the government stepped into the market when private firms could no longer afford to absorb losses. Quasi-public firms were established To preserve the unprofitable lines (Saito, 2015; Shoji, 2001). We believe this intervention may have altered the behaviour of managers at private firms. Because they know that there is a safety net in place if their company cannot sustain losses, they become complacent and do not put in as much effort as expected. Fifth, quasi-public firms implemented cost-cutting measures to reduce their overall financial losses. They "have found that demand is far less than projected," and as a result, they are "doing everything in their power to improve their bottom lines" (Sekiguchi et al., 2010, p. 1286). Lastly, the network infrastructure is not conducive to competition because there can be only one train at a given route halt at any given time. While competition among lines and firms exists on critical intercity routes, its prevalence is limited (F. Mizutani, 1997). Tokyo's urban rail operations are considered a regional monopoly (Kato, 2016).

Policymakers must clarify the objectives of privatisation and liberalisation of the urban rail market. Do they seek improved cost effectiveness? According to the firm's property rights theory, public firms should be less efficient and profitable than private ones (Boardman & Vining, 1989, p. 1). Vining and Boardman (1992) went on to demonstrate that ownership is significant both theoretically and empirically. However, many studies on rail services, such as those by Filippini and Maggi (1993), Lan and Lin (2003), and Canavan (2015), show conflicting findings. We have addressed the differences between these studies (i.e., different samples, different periods, and different kinds of efficiency) that are believed to have resulted in divergent findings. Our findings indicate that private firms performed less well than other firms in terms of cost efficiency.

We have empirically demonstrated in this study that private urban rail firms do not necessarily result in greater cost efficiency. Private firms primarily emphasise maximising profits rather than improving cost efficiency.

8.3 Research Study 3

In Research Study 3 (Chapter 7), we aimed to explore further the ownership effect on each performance dimension (i.e., cost efficiency, service effectiveness and cost effectiveness) in the Japanese urban rail sector and investigate the density, scale, and mode effects on each performance dimension. To achieve these research aims, we set the following research objectives:

a. determine whether private firms are more service effective than other firms,
b. determine whether private firms are more cost-effective than other firms,
c. compare and evaluate private firms' performance in cost efficiency, service effectiveness, and cost effectiveness, and
d. compare and evaluate how density, scale, and mode affect cost efficiency, service effectiveness, and cost effectiveness.

In this study, private firms' cost efficiency from Research Study 2 is used to compare and evaluate private firms' service effectiveness and cost effectiveness.

We concluded that the aims and objectives of this study were met. It has provided a more in-depth understanding of how ownership influences service effectiveness and cost effectiveness in Japan's urban rail sector. It has also provided greater insight into how ownership, density, scale, and mode affect cost efficiency, service effectiveness, and cost effectiveness.

According to the findings obtained in Research Study 2 (Chapter 6), private firms display lower cost efficiency levels than other types of firms (quasi-public and public). However, in this research study, we discovered that private firms outperformed their counterparts regarding service effectiveness and cost effectiveness.

Private firms' higher levels of service effectiveness can be ascribed to their business diversification strategy. Because of this strategy, they have increased and maintained the consumption of urban rail service, which has resulted in improved service effectiveness compared to that of other firms. Another factor that may have contributed to Japanese private urban rail firms' greater service effectiveness is the tendency of other firms, particularly quasi-public firms, to operate their services at the bare minimum level of expected service, notwithstanding low service consumption. Many of these firms have confronted a situation in which the demand for services is far lower than anticipated (Sekiguchi et al., 2010, p. 1286).

Mizutani (1994) explained why private Japanese urban rail firms were more cost-effective. Private firms outperformed other firms in various areas, including faster travel, lower fares, higher labour productivity, and a lower average employee wage.

One convincing argument favouring private urban rail firms in Japan being more cost-effective is that these firms are profit-maximising entities. It may explain why our findings on the cost effectiveness performance of Japanese private urban rail firms are comparable to those of Mizutani (1994), even though our research was done more than a decade apart.

The aim of private owners to gain a return on their investment creates ongoing pressure on business managers to perform effectively, as we theorised in the Literature Review: The Performance of Private Firms section (Chapter 2). Private owners might have benefited from Japan's Railway Accounting Regulations, which differentiate between rail lines and non-rail businesses in financial reporting. Furthermore, quasi-public and public firms that place a high value on social welfare may not have put forth the same effort as private firms in pursuing profit maximisation.

The principal-agent problem, which is relatively less severe in the private sector, may have also contributed to the superior cost effectiveness of Japanese private urban rail firms compared to quasi-public and public firms.

Our study also revealed that, except for population density, different factors have varying degrees of influence on each performance dimension. Ownership, traffic density, scale, mode, and time affect cost efficiency, service effectiveness, and cost effectiveness differently. Our findings are consistent with the study carried out by Karlaftis and Tsamboulas (2012), which arrived at a similar conclusion that the performance of a system in a particular area, such as cost efficiency, does not necessarily indicate its success in another area, such as service effectiveness. These findings are also consistent with Kerstens (1996), who discovered that the performance of public transit systems varied greatly depending on the output specification utilised. We believe that a complete understanding of urban rail performance can be reached by first analysing all performance aspects (i.e., cost efficiency, service effectiveness and cost effectiveness) and then interpreting the results of these evaluations concerning one another.

8.4 Main Research Contributions

We believe our studies have given some valuable insights into measuring the performance of urban rail services. We want to highlight five main research contributions.

First, traffic density and scale affect different performance dimensions (i.e., cost efficiency, service effectiveness and cost effectiveness) in different ways. Traffic density and scale are significant factors for measuring urban rail performance in cost efficiency and service effectiveness but are less significant when measuring cost effectiveness. In Japan, even though a higher traffic density may result in better cost efficiency, it may lead to lower service effectiveness and not improve cost effectiveness. The same applies to scale. The fact that cost efficiency has improved over time could mean that urban rail firms are getting better at what they do.

Nonetheless, they have difficulty generating sufficient additional service consumption. Modal shifts and an ageing population have hurt service consumption, according to Jitsuzumi and Nakamura (2010). Apart from ours, we have never encountered a study that evaluates traffic density and scale on all performance dimensions (cost efficiency, service effectiveness and cost effectiveness). Therefore, we look forward to seeing more findings in this area.

Second, mode affects different performance dimensions in different ways. We found that mode difference is a significant factor for measuring the urban rail performance in cost efficiency and service effectiveness but less significant when measuring cost effectiveness. From another angle, the mode difference is significant between under-ground and over-ground, and between under-ground and monorail. However, it is less significant between the monorail and over-ground across all performance dimensions. Additionally, we found that just because one mode performs best in one performance dimension does not mean it serves best in another. For example, under-ground has the weakest cost efficiency but the most substantial service effectiveness. We believe that different technological characteristics such as train size, capacity and length may require additional maintenance amounts but simultaneously offer different levels of benefit. We have discussed several policy implications in Research Study 1. Our findings concur with those of Savage (1997), who concentrated on the operating costs of urban rail modes in the United States. Considering the findings by Graham (2008), Ingvardson and Nielsen (2018), Min et al. (2017), and Tsai et al. (2015) — who discovered that urban rail modes differed in terms of production — we recommend stating and recognising mode difference in future urban rail studies.

Third, RTD and RTS vary between over-ground, monorail, and under-ground. Many authors such as Keeler (1974), Savage (1997), Mizutani (2004), Graham (2008) and Brage-Ardao et al. (2015) found that rail services (including urban rails) exhibit increasing RTD but constant RTS for cost efficiency. Our findings offer more insights. We discovered that over-ground, monorail, and under-ground all have different rates of increase for RTD, although there is no significant difference between monorail and under-ground. We further discovered that over-ground and under-ground show constant RTS, although there is no significant difference between the two. Monorail, on the other hand, shows increasing RTS.

Fourth, private firms are profit-maximising entities but not necessarily cost-efficiency maximisers. Our finding on the cost effectiveness of the Japanese private urban rail firms is very similar to that of Mizutani (1994), who also found that Japanese private urban rail firms are more cost-effective than other firms. Despite being more than a decade apart, these consistent empirical findings reaffirm the economic theories on private firms' profit maximisation behaviour that we explained in the Literature Review: The Performance of Private Firms section (Chapter 2). On the other hand, our finding on the Japanese private urban rail firms' cost efficiency suggests that private urban rail firms are not necessarily cost efficiency maximisers[2]. This perspective is supported by Canavan (2015), who talked about the differences between private and public incentives when he found that private firms are less efficient than public firms. Private firms may be more likely to cut back on services to make the most money.

Fifth, measuring all the performance dimensions and interpreting the results relative to each other is essential. It will give a comprehensive

[2] We have identified several possible reasons why Japanese private urban rail firms are less cost-efficient than the others in Research Study 2.

understanding of the performance of the urban rail service under evaluation. Research Study 3 has shown that ownership, traffic density, scale, mode, and time affect cost efficiency, service effectiveness, and cost effectiveness differently. We want to reiterate that using only one performance dimension in one's research may show a partial picture of the overall performance. Also, the goals policymakers hope to accomplish through engaging private firms in the urban rail market should be articulated clearly. Do they want to achieve self-sufficiency, improve cost efficiency, improve service effectiveness, or improve cost effectiveness? This thesis has demonstrated empirically that improved cost effectiveness is achievable, but improved cost efficiency is not guaranteed by having private firms operating in the urban rail market.

8.5 Research Limitations and Suggestions for Future Research

We have identified several limitations that should be taken into consideration when interpreting the results. These limitations highlight areas where further research is needed to enhance the validity and generalisability of our findings. Additionally, we have formulated some suggestions based on these limitations, which aim to address the identified shortcomings and provide potential avenues for future research. They are discussed as follows:

The Interpretation of Mode and Ownership Roles in Performance

In Research Studies 2 and 3, both mode and ownership variables were included to investigate the performance differences between private firms and other firms in Japan's urban rail services, considering mode differences. Private firms primarily focused on over-ground operations, while other firms concentrated on monorail and underground operations (see Table 10 on page 88). Mizutani (1994, p. 168) also found a similar correlation when assessing the cost effectiveness of urban rail services in Japan, stating that this correlation "should not cause bias in the coefficients". Additionally, when the ownership variable was added to the model used in Research Study 1, which already contained the mode variable, no significant changes in the coefficients were observed.

Although coefficient bias is not a concern, the interpretation of the findings is not straightforward and may require further research. This is because only one private firm represented each monorail and underground operation, which could lead to interpreting the findings as individual firm performance relative to other firms. This highlights the challenge of conducting empirical studies when the market composition may not be ideal statistically. Despite the sample limitations, we still were able — to some extent — to disentangle the various factors in the regression (i.e., adding the ownership variable did not greatly change the mode effects). To gain a deeper understanding of the performance of private firms in monorail and underground operations, we propose conducting more detailed research, such as a case study on the firms involved.

Mode Separation[3] as An Alternative to Mode Recognition[4]

Perhaps one alternative in addressing mode and ownership correlation is to conduct separate analysis for each rail mode. The separation approach involves dividing the heterogeneous data sample into homogeneous subsamples and conducting separate analyses for each subsample (Holý, 2022). Here, ownership variable is included in the model while mode variable is excluded from the model. However, separating the analysis reduces the sample size for each model. As stated by Holý (2022), this approach is simple and easy to interpret but may reduce the sample size significantly, limiting its applicability in some studies. Specifically, a cost or production function necessitates a substantial dataset in order to obtain reliable outcomes, preferably utilizing panel data to account for unobserved variations (Karlaftis & Tsamboulas, 2012). Our research involved trans-log cost function and

[3] Separating rail modes before evaluating operators
[4] Addressing mode difference through the use of variables such as dummies

DEA-Tobit regression models, which require a large sample size for reliable results. With this in mind, we recommend a comparative study on both approaches (mode separation and mode recognition) to evaluate differences in the results.

On another note, we believe that applying the separation approach will not address the challenge in interpreting the performance of private firms in the Japanese monorail and under-ground operations since the number of private firms in the respective rail mode categories remains the same.

More Granular Data for Population Density, and Inclusion of Other Potential Variables

We treated population density as the number of persons per 1km^2 in the prefecture(s) where a firm is serving. We note that in some cases, a firm serves only certain parts of their serviced prefecture(s). This is a challenge we faced when obtaining data on population density. Although we believe it may not change the coefficient sign, we recommend future research uses population density data at the municipal level for more accurate results.

In addition to that, incorporating additional potential factors such as the quantity of stations, service quality and car ownership (at the municipal level) can enhance the accuracy of the findings. Considering the number of stations can provide insights into the accessibility and availability of urban rail services. Similarly, a higher level of service quality may encourage more individuals to choose urban rail services. Car ownership at the municipal level can indicate the reliance on private vehicles and potentially influence the demand for urban rail services. We suggest considering these potential factors when data accessibility is not a constraint.

DEA-Tobit regression and trans-log cost function limitations

The DEA-Tobit regression and the trans-log Cost Function approaches possess certain advantages in assessing efficiency and identifying key factors. However, it is important to recognise their limitations. The DEA-Tobit regression approach requires a large sample size to obtain reliable efficiency estimates. When dealing with small sample numbers, efficiency evaluations may be unstable and prone to being influenced by extreme values (Anang, 2022). The trans-log cost function assumes that coefficients are constant over time. This assumption may not be true since the cost function coefficients can vary across different time periods (Kuroda, 1995). To overcome this limitation, scholars have included time-varying factors in the trans-log cost function. However, this methodology requires significant data collection for precise estimation. Furthermore, trans-log cost function relies on a predetermined functional form, such as the Cobb-Douglas production function, as discussed by W. Thuo and M. Ndagara (2021). Nevertheless, it is important to note that any particular functional form may not accurately represent the intricacies of the production process across various sectors or industries. Different divergent industries may have unique production functions, and implementing a standard set functional structure could lead to biased cost predictions.

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Appendix A: Further Details on Japan Urban Rail Environment and Data

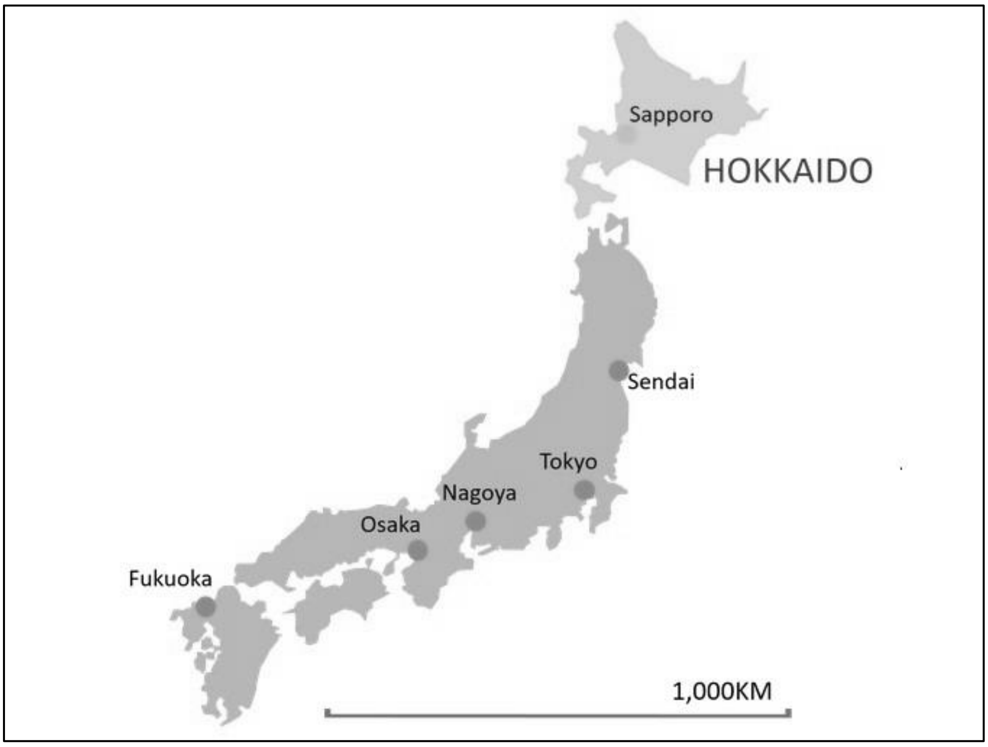

Figure 19. Major Metropolitan Areas in Japan

Table 37. Japan Urban Rail Firms and Their Service Locations

ID	*Name*	*Metropolitan Area*	*Metropolitan Prefectures*[1]	*Serviced Prefectures*[2]
1	Tobu (Tōbu Railway)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Tokyo, Saitama, Chiba, Gunma, Tochigi
2	Seibu (Seibu Railway)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Tokyo, Saitama
3	Keisei (Keisei Electric Railway)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Tokyo, Chiba
4	Keio (Keiō Corporation)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Tokyo, Kanagawa
5	Odakyu (Odakyū Electric Railway)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Tokyo, Kanagawa

[1] Metropolitan prefectures are the prefectures located in the said metropolitan area.
[2] Serviced prefectures are the prefectures in which the said urban rail firm runs its services.

ID	*Name*	*Metropolitan Area*	*Metropolitan Prefectures*[1]	*Serviced Prefectures*[2]
6	Tokyu (Tōkyū Corporation)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Tokyo, Kanagawa
7	Keikyu (Keihin Electric Express Railway)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Tokyo, Kanagawa
8	Soutetsu (Sagami Railway (Sōtetsu))	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Kanagawa
9	Meitetsu (Nagoya Railroad)	Nagoya (Chūkyō)	Aichi, Gifu, Mie	Aichi, Gifu
10	Kintetsu (Kintetsu Railway)	Nagoya (Chūkyō)	Aichi, Gifu, Mie	Osaka, Nara, Kyoto, Aichi, Mie
11	Nankai (Nankai Electric Railway)	Keihanshin	Osaka, Kyoto, Hyōgo, Nara, Shiga, Wakayama	Osaka, Wakayama
12	Keihan (Keihan Electric Railway)	Keihanshin	Osaka, Kyoto, Hyōgo, Nara, Shiga, Wakayama	Osaka, Kyoto, Shiga

ID	*Name*	*Metropolitan Area*	*Metropolitan Prefectures*[1]	*Serviced Prefectures*[2]
13	Hankyu (Hankyū Corporation)	Keihanshin	Osaka, Kyoto, Hyōgo, Nara, Shiga, Wakayama	Kyoto, Osaka, Hyōgo
14	Hanshin (Hanshin Electric Railway)	Keihanshin	Osaka, Kyoto, Hyōgo, Nara, Shiga, Wakayama	Osaka, Hyōgo
15	Nishitetsu (Nishi-Nippon Railroad)	Fukuoka–Kitakyushu	Fukuoka	Fukuoka
16	Tokyo Metro (Tokyo Metro)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Tokyo, Chiba, Saitama
17	Shinkeisei (Shin-Keisei Electric Railway)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Chiba
18	Tokyo monorail (Tokyo monorail)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Tokyo
19	Senboku (Semboku Rapid Railway)	Keihanshin	Osaka, Kyoto, Hyōgo, Nara, Shiga, Wakayama	Osaka

ID	*Name*	*Metropolitan Area*	*Metropolitan Prefectures*[1]	*Serviced Prefectures*[2]
20	Kobe (Kōbe Electric Railway)	Keihanshin	Osaka, Kyoto, Hyōgo, Nara, Shiga, Wakayama	Hyōgo
21	Sanyo (Sanyo Electric Railway)	Keihanshin	Osaka, Kyoto, Hyōgo, Nara, Shiga, Wakayama	Hyōgo
22	Nose (Nose Electric Railway)	Keihanshin	Osaka, Kyoto, Hyōgo, Nara, Shiga, Wakayama	Hyōgo, Osaka
23	Hokushin (Hokushin Kyūkō Electric Railway)	Keihanshin	Osaka, Kyoto, Hyōgo, Nara, Shiga, Wakayama	Hyōgo
24	Kita Kyushu (Kitakyushu Monorail)	Fukuoka–Kitakyushu	Fukuoka	Fukuoka
25	Saitama new transit (Saitama New Urban Transit)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Saitama
26	Saitama Rapid (Saitama Railway)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Saitama, Tokyo

ID	*Name*	*Metropolitan Area*	*Metropolitan Prefectures*[1]	*Serviced Prefectures*[2]
27	Hokuso (Hokusō Railway)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Tokyo, Chiba
28	Chiba monorail (Chiba Urban Monorail)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Chiba
29	Yokohama seaside (Yokohama New Transit)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Kanagawa
30	Yurikamome (Yurikamome)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Tokyo
31	Tokyo rinkai (Tokyo Waterfront Area Rapid Transit)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Tokyo
32	Toyo rapid (Tōyō Rapid Railway)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Chiba
33	Tama monorail (Tama Toshi Monorail)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Tokyo

ID	*Name*	*Metropolitan Area*	*Metropolitan Prefectures*[1]	*Serviced Prefectures*[2]
34	Yokohama rapid (Yokohama Minatomirai Railway)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Kanagawa
35	Kita Osaka (Kita-Osaka Kyūkō Railway)	Keihanshin	Osaka, Kyoto, Hyōgo, Nara, Shiga, Wakayama	Osaka
36	Kobe new transit (Kobe new transit)	Keihanshin	Osaka, Kyoto, Hyōgo, Nara, Shiga, Wakayama	Hyōgo
37	Osaka monorail (Osaka monorail)	Keihanshin	Osaka, Kyoto, Hyōgo, Nara, Shiga, Wakayama	Osaka
38	Sapporo (Sapporo City Transportation Bureau)	Sapporo	Ishikari Subprefecture in Hokkaidō	Hokkaido
39	Sendai (Sendai Subway)	Sendai	Miyagi	Miyagi
40	Tokyo subway (Toei Subway)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Tokyo, Chiba

ID	Name	Metropolitan Area	Metropolitan Prefectures[1]	Serviced Prefectures[2]
41	Yokohama sub (Yokohama Municipal Subway)	Tokyo (Kantō)	Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Yamanashi	Kanagawa
42	Nagoya sub (Nagoya Municipal Subway)	Nagoya (Chūkyō)	Aichi, Gifu, Mie	Aichi
43	Kyoto sub (Kyoto Municipal Subway)	Keihanshin	Osaka, Kyoto, Hyōgo, Nara, Shiga, Wakayama	Kyoto
44	Osaka sub (Osaka Metro)	Keihanshin	Osaka, Kyoto, Hyōgo, Nara, Shiga, Wakayama	Osaka
45	Kobe sub (Kobe Municipal Subway)	Keihanshin	Osaka, Kyoto, Hyōgo, Nara, Shiga, Wakayama	Hyōgo
46	Fukuoka (Fukuoka City Subway)	Fukuoka–Kitakyushu	Fukuoka	Fukuoka

Appendix B: Specification of a Functional Form

1. Background

A cost function regression can shed light on the cost structure of each rail mode, providing insight into density and scale. Chapter 3 discusses two main functional forms in the literature when estimating cost functions: Cobb Douglas and trans-log. These polynomial cost functions can accommodate microeconomic theories (Reynès, 2011).

As discussed earlier, the trans-log model is typically favoured over the Cobb-Douglas model when it comes to estimating a cost function since the former allows for more variations on the explanatory side (Smith et al., 2017). It enables the cost elasticity to be dynamic, allowing for more accurate economic interpretations of the cost structure.

However, the trans-log cost function requires a functional form to be specified (Nash & Smith, 2014). This procedure determines a suitable functional form for the model, selects the variables to be incorporated, and adapts economic theories. The demanding task makes implementing the trans-log cost function more challenging than the DEA-Tobit regression[1].

To focus the discussion on the key results of Research Study 1 (Chapter 5), this appendix first deals with the extensive work to select the preferred model. The reason for devoting significant space to this aspect is that selection is not a simple binary choice between a Cobb-Douglas or trans-log, given the mode dummies we included in the model, as explained below. We aim to produce a trans-log cost function model through a robust model selection process. The results from this model will be utilised in Research Study 1 (Chapter 5) and Research Study 2 (Chapter 6).

[1] We will compare the results from DEA-Tobit regression model to those of Trans-log Cost Function model in Research Study 2.

2. Imposing Homogeneity of Degree One in Prices

We assumed firms could respond to any change in input price by adjusting their input mix (i.e., the slope iso-cost line is the same as the slope of the iso-quant curve). It means that if all input prices double, costs should double[2]. It is a theoretical requirement of a cost function. This practice is common for the cost function models (Coelli et al., 2005). Other authors who imposed the same condition include Savage (1997), Mizutani (2004), Couto and Graham (2008), Wheat and Smith (2015), and Anupriya et al. (2020). Therefore, we imposed homogeneity of degree one in prices by dividing the operating costs and the input prices by one of the input prices as follows:

$$Ln\left(\frac{C_{ELM}}{P_M}\right) = \beta_{P_E} Ln\left(\frac{P_E}{P_M}\right) \times \beta_{P_L} Ln\left(\frac{P_L}{P_M}\right) \times \beta_{P_M} Ln\left(\frac{P_M}{P_M}\right)$$

Note that the above equation illustrates the homogeneity of degree one in prices. Output and other variables are also in the cost function.

i. Comparing the Trans-log Model over the Cobb-Douglas model

We assessed whether or not the trans-log model was statistically better than the Cobb-Douglas model. We added the trans-log terms to the Cobb-Douglas model to do so. The trans-log terms consist of the squared and interaction terms for every base variable (i.e., traffic density, energy price, labour price, maintenance price, and network length). Then, we conducted an F-test on the squared and interaction term coefficients (see Table 38 on page 201). With 95% confidence, we found that the inclusion of the trans-log terms to the Cobb-Douglas model would produce a statistically better model. Thus, we proceeded with the trans-log model.

[2] since the required output is held fixed and the optimal input mix will not change (as all inputs have increased by the same proportion).

Table 38. F-test on the Trans-log terms

No.	H_0	Prob>F	α	Remark
1	$\beta_{D_tD_t} = \beta_{D_tP_E} = \beta_{D_tP_L} = \beta_{D_tP_M} = \beta_{D_tN} = 0$	0.000	5%	Including squared and interaction terms for *traffic density* offers a better explanation.
2	$\beta_{D_tP_E} = \beta_{P_EP_E} = \beta_{P_EP_L} = \beta_{P_EP_M} = \beta_{P_EN} = 0$	0.000	5%	Including squared and interaction terms for *energy price* offers a better explanation.
3	$\beta_{D_tP_L} = \beta_{P_EP_L} = \beta_{P_LP_L} = \beta_{P_LP_M} = \beta_{P_LN} = 0$	0.000	5%	Including squared and interaction terms for *labour price* offers a better explanation.
4	$\beta_{D_tP_M} = \beta_{P_EP_M} = \beta_{P_LP_M} = \beta_{P_MP_M} = \beta_{P_MN} = 0$	N/A	N/A	These terms were eventually excluded since the material price is treated as the denominator for linear homogeneity.
5	$\beta_{D_tN} = \beta_{P_EN} = \beta_{P_LN} = \beta_{P_MN} = \beta_{NN} = 0$	0.000	5%	Including squared and interaction terms for *network length* offers a better explanation.
6	All terms tested together	0.000	5%	Including all squared and interaction terms for all variables offers a better explanation.

ii. Expanding the Trans-log Model

We then gradually included the mode dummy intercepts and interactions in the base model. The inclusion of these additional terms served several purposes. First, the mode dummy intercepts were included to observe the general cost differences between modes. Second, the mode dummy interactions with traffic density and network length were included to produce dedicated cost elasticity for each rail mode. Each rail mode would have its cost elasticity lines w.r.t density and w.r.t scale. Third, the mode dummies interactions with the squared terms for traffic density and network length were included to allow the variation in the cost elasticity w.r.t those variables to differ by rail mode. It means that the cost elasticity lines w.r.t density and w.r.t scale may have different curvatures for each rail mode. Last, the mode dummy interactions with the remaining variables in the equation were included to observe whether the model could gain more explanatory power.

Table 39 on page 203 shows the model progression — from the base to the rich model (with full-mode dummy intercepts and interactions). As the model progressed, we conducted the F-test, AIC, and BIC to check the model strength (see Table 40 on page 205).

The RTD and RTS could then be derived by solving the inverse of the Cost Elasticity w.r.t Density (CED) and the Cost Elasticity w.r.t Scale (CES). With this information, we would be able to evaluate the cost structure of each rail mode.

3. Selecting A Model

The F-test, AIC, and BIC results suggested that the model improved as more terms were added. All of these measures produced the same conclusion regarding model selection. Model 12 (the rich model), which contained full dummy intercepts and interactions, was the best. Our initial preference was Model 12 because even the BIC, supposedly the most cautious[3] among the three in recommending additional parameters, presented its lowest number. Table 40 on page 205 shows the results of the fitness tests, and Table 48 on page 227 shows the regression results for Model 12.

[3] The term $k * \ln(n)$ in BIC generates a greater positive number compared to the term $2k$ in AIC as the k (number of parameters) increases. Therefore, BIC has less tendency to recommend models with many terms or interactions than the AIC does. The F-test works differently and does not have such a term but does require statistical significance.

Table 39. Trans-log Progression

TERMS	Base --> Rich											
	Model Number											
	1	2	3	4	5	6	7	8	9	10	11	12
Homogeneity of Degree One	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mode dummy intercepts		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mode dummy-traffic density interactions			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mode dummy-network length interactions				✓	✓	✓	✓	✓	✓	✓	✓	✓
Mode dummy-traffic density squared interactions					✓	✓	✓	✓	✓	✓	✓	✓
Mode dummy-network length squared interactions						✓	✓	✓	✓	✓	✓	✓
Mode dummy-traffic density-network length interactions							✓	✓	✓	✓	✓	✓
Mode dummy-input price interactions								✓	✓	✓	✓	✓

TERMS	Base --> Rich											
	Model Number											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Mode dummy-input price squared interactions									✓	✓	✓	✓
Mode dummy-input price a-input price b interactions										✓	✓	✓
Mode dummy-traffic density-input price interactions											✓	✓
Mode dummy-network length-input price interactions												✓

Note: Base = Trans-log without mode dummy intercepts and interactions; Rich = Trans-log with full mode dummy intercepts and interactions. Terms are added as the model progresses from 1 to 12. For example, Model 8 contains all the terms in Model 7, plus the mode dummy-input price interactions. Model 12 contains all the terms listed.

Table 40. Model Fit Diagnostics

Test	*Model*											
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
R^2	0.981	0.984	0.985	0.987	0.988	0.989	0.989	0.990	0.991	0.991	0.992	0.992
F		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	-244.9	-327.5	-379.3	-443.5	-491.5	-520.7	-533.3	-559.7	-595.7	-616.9	-656.3	-680.5
BIC	-180.2	-254.2	-297.3	-353.0	-392.3	-412.9	-416.9	-426.0	-444.7	-457.3	-479.5	-486.4

Nevertheless, statistical testing is not the sole factor to be considered. The model selection process entails evaluating the goodness of fit measures and ensuring that the selected model is conceptually sound, particularly regarding the elasticities in this case. The trans-log model is widely recognised for its potential to involve many parameters for estimation. This issue is further compounded in this case due to the inclusion of mode dummies and potential interactions. A complex trans-logarithmic model may yield outcomes that are challenging to comprehend or seemingly unrealistic. Therefore, a drive exists to seek a parsimonious and sensible model in terms of elasticities, as Wheat and Smith (2015) discussed.

We further looked into the CED and the CES, as these were the two elements of interest in the study. We evaluated whether Model 12 produced intuitive CED and CES curves for each rail mode.

i. CED

Figure 20 on page 207 shows a scatter plot of CED, which did not hold other variables at their mean values. It can be observed that there is a considerable number of over-ground's CED values that sat over the unitary line at lower density values[95]. It means the percentage cost increase was more than the percentage density increase for that portion of the sample. Hence, the average cost curve would not be the typical U-shape. Rather, it would be an inverse U-shape. One concern with Model 12 (the rich model) was that the curve of CED for the over-ground mode was not intuitive from the economics perspective (see Figure 21 on page 207). It was downward sloping and started at a value of more than 1 (unitary).

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[95] We were not concerned with the under-ground's cost elasticity w.r.t density that sat below zero because they disappeared when we plotted the cost elasticity w.r.t density while holding other variables at their mean values. This meant that the negative values might have been influenced by variables or factors other than density.

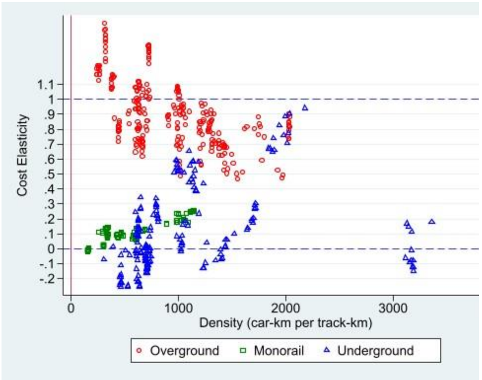

Figure 20. CED by Rail Mode (without holding other variables at their mean values) from Model 12

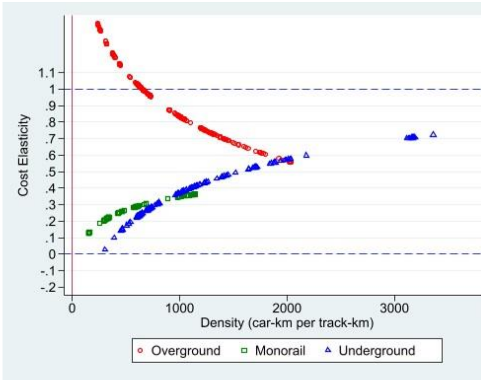

Figure 21. CED by Rail Mode (holding other variables at their mean values) from Model 12

For illustration, we set ¥1 Million as the initial operating costs for each rail mode. Applying the aforementioned CED for each rail mode, we would get the average cost curves w.r.t density, as shown in Figure 22 on page 207. The average cost curve for the over-ground could be seen as an inverse U. On the other hand, the average cost curves for the monorail and the under-ground could be seen as a part of U.

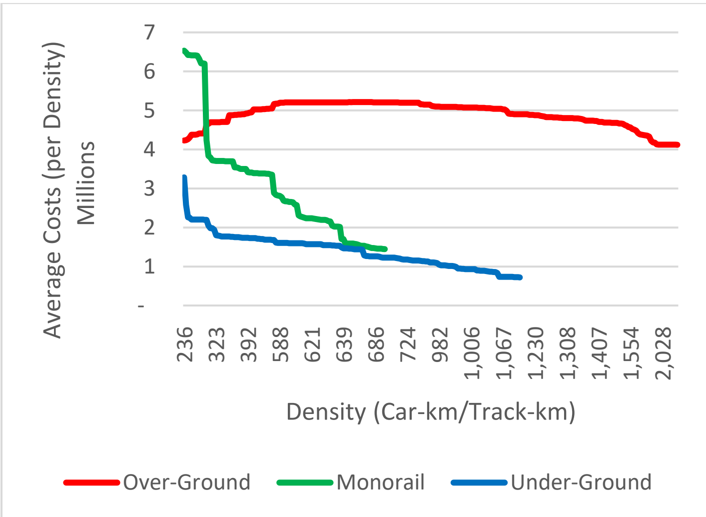

Figure 22. An Illustration on Average Costs per Density by Rail Mode

Table 41 on page 208 shows the significance of the second-order density term for each rail mode from Model 12. This term determined the variation of CED and the shape of the average cost curve for each rail mode. From this table, we can see that Model 12 suggested that the semi-U shape curve for the monorail was significant, but the semi-U shape curve for the under-ground was insignificant[96]. The inverse U shape curve for the over-ground's average cost curve was significant. We found that the suggested significance for the inverse U shape average cost curve was not intuitive from the economics perspective.

Table 41. The Significance of the Second Order Density Term by Rail Mode from Model 12

Mode	**Coefficient of the 2nd Order Term relative to the equation**	**Prob > F**	**Remark**
Over-ground (omitted condition)	$\beta_{D_tD_t} = -0.3903217$	0.0000	Significant at 0.05 level
Monorail	$\beta_{D_tD_t} + \beta_{D_tD_tD_{MM}} = -0.3903217 + 0.5081545 = 0.1178328$	0.0292	Significant at 0.05 level
Under-ground	$\beta_{D_tD_t} + \beta_{D_tD_tD_{MU}} = -0.3903217 + 0.6806861 = 0.2903644$	0.0966	Insignificant at 0.05 level

ii. CES

Figure 23 on page 209 shows a scatter plot of CES, which did not hold other variables at their mean values for Model 12. This time, the over-ground's CES sat over the unitary line at lower scale values. It means the percentage cost increase was more than the percentage scale increase. The curve of CES for the over-ground mode was also not intuitive from the economics perspective (see Figure 24 on page 209). The average cost curve would not be the typical U shape but an inverse U shape.

[96] At 0.05 significance level.

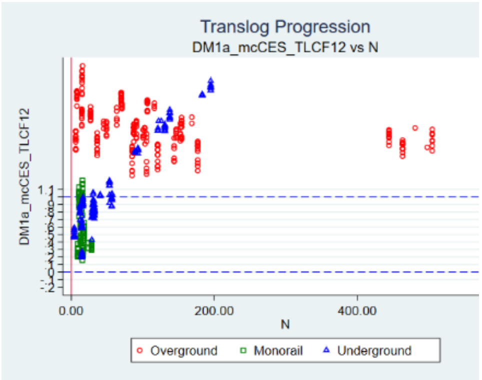

Figure 23. CES by Rail Mode (without holding other variables at their mean values) from Model 12

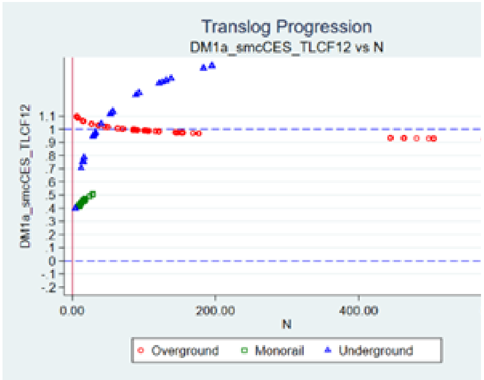

Figure 24. CES by Rail Mode (holding other variables at their mean values) from Model 12

Table 42. The Significance of the Second Order Scale Term by Rail Mode from Model 12

Mode	Coefficient of the 2nd Order Term relative to the equation	Prob > F	Remark
Over-ground (omitted condition)	$\beta_{NN} = \ -0.0379035$	0.0111	Significant at 0.05 level
Monorail	$\beta_{NN} + \beta_{NND_{MM}} = -0.0379035 + 0.1162777 = \ 0.0783742$	0.6075	Insignificant at 0.05 level
Under-ground	$\beta_{NN} + \beta_{NND_{MU}} = -0.0379035 + 0.3189083 = \ 0.2810048$	0.0010	Significant at of 0.05 level

Table 42 on page 209 shows the significance of the second-order scale term for each rail mode from Model 12. This term determined the variation of CES and hence, the shape of the curve for each rail mode.

This table shows that Model 12 suggested that the convexity[97] for the over-ground curve is significant. To sum up, not only did Model 12 suggest counter-intuitive average cost curves w.r.t density and scale for the over-ground, but the model also suggested a counter-intuitive significance for the said curves.

4. Towards A Plausible Model

We took a few steps back and looked at Model 6. This model included the mode dummy intercepts and mode dummy interactions without being overly specified. The mode dummies interacted with the first and second-order terms for the traffic density and the network length variables — enough for us to derive variations in the Returns to Density (RTD) and the Returns to Scale (RTS). There were no further mode dummy interactions, which were indeed unnecessary. It placed Model 6 close to parsimony. The terms included in Model 6 can be found in Table 39 on page 203.

Like Model 12, Model 6 had the same downward-sloping CED curve for the over-ground (see Figure 25 on page 211). But unlike Model 12, Model 6 had this curve start at 0.9992713, less than 1 (unitary). We could imagine that the average cost curves for the over-ground would be a part of inverse U (if, for example, the over-ground elasticity curve was extrapolated, the elasticity could start above unity and then falls). However, Model 6 suggested that the downward movement of the CED for the over-ground was insignificant (as opposed to being significant in Model 12).

[97] As illustrated earlier, this convexity produced an inverse U-shaped average cost curve which was not intuitive from the economics perspective.

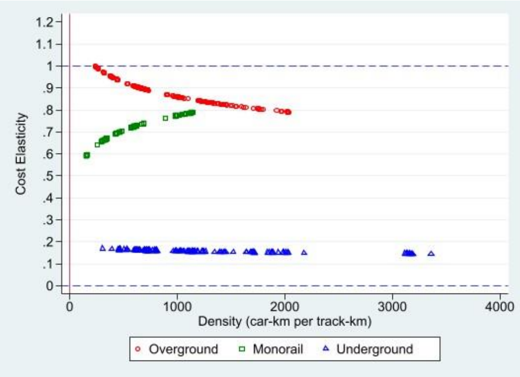

Figure 25. CED by Rail Mode from Model 6

Table 43 on page 212 shows the significance of the second-order density term for each rail mode from Model 6. From this table, we could translate that the shape[98] of the CED curve for the over-ground was insignificant[99]. In other words, we could say that although Model 6 generated a counter-intuitive shape (if extrapolated) for the over-ground's average cost curve, the model suggested this shape was not of concern. It was sensical from the economics point of view. Considering this and its closeness to parsimony, we opined that Model 6 would be the most suitable model to implement. The regression results for Model 6 can be found in Table 49 on page 228.

In the later section, we purged all the insignificant dummy interactions, followed by the insignificant density and scale variables (i.e., Density, Density^2, Network, Network^2). By doing so, we managed to get CED and CES graphs which were easier to explain. We then purged some other insignificant variables to make the shortlisted models more efficient.

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98 The shape of the curve was determined by the second order terms, which allowed variation in the cost elasticity.

99 At 0.05 significance level. We could also see that the same applied to the monorail. Yet in the case of monorail rail, the insignificance simply meant the well-behaved curve was not an important influence on the costs. Therefore, the finding on the monorail's curve was not counter-intuitive from the economics perspective.

Table 43. The Significance of the Second Order Density Term by Rail Mode from Model 6

Mode	Coefficient of the 2nd Order Term relative to the equation	Prob > F	Remark
Over-ground (omitted condition)	$\beta_{D_tD_t} = -0.0968506$	0.1095	Insignificant at 0.05 level
Monorail	$\beta_{D_tD_t} + \beta_{D_tD_tD_{MM}} = -0.0968506 + 0.1952834 = 0.0984328$	0.1437	Insignificant at 0.05 level
Under-ground	$\beta_{D_tD_t} + \beta_{D_tD_tD_{MU}} = -0.0968506 + 0.0866719 = -0.0101787$	0.9465	Insignificant at 0.05 level

i. Selecting the Estimator

We conducted three types of tests to identify the most suitable estimator among the Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE). The tests were:

- F-test (to see whether the FE was better than the OLS),
- Breusch Pagan LaGrange Multiplier test (to see whether the RE was better than the OLS), and
- Hausman test (to see whether the FE was better than the RE).

The results are summarised in Table 44 on page 213. The F-test found that the Individual specific effects were not zero and recommended the FE over the OLS estimator. The Breusch Pagan LaGrange Multiplier test found that panel effects were not zero and recommended the RE over the OLS. The Hausman Test found that the coefficient difference was not zero and recommended the FE over the RE. Based on these results, we concluded that the best estimator for Model 6 was the FE, consecutively followed by the RE and the OLS.[100]

Table 44. Tests on the Method of Estimation

Test	*Result*	*α*	*Conclusion*
F-test for the Fixed Effects	Individual-specific effects were not zero	0.05	The FE was recommended over the OLS.
Breusch Pagan Lagrangian Multiplier test	Panel effects were not zero	0.05	The RE was recommended over the OLS.
Hausman test	The difference in coefficients was not zero	0.05	The FE was recommended over the RE.

However, one limitation of the FE was that it did not allow any inclusion of time-invariant variables. The time-invariant mode dummies were needed in Model 6 to assess whether the overall costs would differ between rail modes. Moreover, we found that the FE did not produce intuitive results (see Refining the Model). For this reason, we opined that the RE was the most suitable estimator among the three. It allowed the use of time-invariant variables and was better than the OLS.

ii. Refining the Model

We introduced a time trend to the model to observe whether time affected the cost. We also introduced the second-order term for time,

[100] For the purpose of control, we took Model 12 (which contained full dummy intercepts and interactions) and applied the same procedures. We found that all models did not produce intuitive results. We also found that all tests on the method of estimation for Model 12 produced the same results and recommendations as they did for Model 6. We derived two conclusions from this control procedure. One, Model 6 was the preferred model over Model 12 because of its intuitive results. Two, the tests we used provided consistent recommendations.

Time^2, for the same reason[101]. After that, for comparison, we regressed using three methods of estimation: the Ordinary Least Squares (OLS), the Fixed Effects (FE), and the Random Effects (RE). All and all, we had nine Model 6 variants as follows:

- Model 6 OLS
- Model 6 OLS +Time
- Model 6 OLS +Time +Time^2
- Model 6 FE
- Model 6 FE +Time
- Model 6 FE +Time +Time^2
- Model 6 RE
- Model 6 RE +Time
- Model 6 RE +Time +Time^2

These models produced different CED and different CES (CES) graphs. They also assigned different levels of significance[102] to the coefficients. The results from these models were tabulated in Table 52 on page 234. The table also contained our observations. In general, we found that some models produced intuitive[103] results on both CED and CES, others produced intuitive results only on one dimension (either CED or CES), and some did not produce any intuitive results on both CED and CES curves.

Under the FE estimation, we could see that Model 6 (with and without the time variable) did not generate intuitive CED and CES graphs. For example, the curvature of the CED line for the under-ground (DMU) — which contained many negatives — was significant. It violated the monotonicity condition that required the costs to be non-decreasing in

---

[101] After adding Time and Time^2 variables, we had three models: Model 6, Model 6 +Time, and Model 6 +Time +Time^2.

[102] For the purpose of standardisation across assessments, we set the significance level at 0.05.

[103] In accordance with microeconomics theory. In general, a cost elasticity curve should be concave, positive in values, and starting with values below unitary line.

output. Another example is the curvature of the CES line for the underground (DMU) — which made the line concave up — which was deemed significant. It produced an abnormal average cost curve that would be concave down or inverse 'u'.

Under the OLS estimation, we could see that Model 6 (with and without the time variable) generated intuitive CED and CES graphs. The curvature of CED lines for the over-ground (DMO) and the underground (DMU), which made the lines concave up, was insignificant.

Under the RE estimation, we could see that Model 6 (with time variable) also generated intuitive CED and CES graphs. The curvature of CED and CES lines for the over-ground (DMO) made the lines start at a point above unitary and concave up. It would have produced abnormal average cost curves (concave down or inverse U shape). However, this situation was ruled out by the insignificant status of the curvature. Without the time variable, the curvature of the CED line became significant and would produce an abnormal average cost curve. Therefore, we decided that Model 6 OLS and Model 6 RE +Time[104] would be the most sensical for further refinement as they produced intuitive CED and CES graphs.

Considering we have a panel data set, we regenerated the nine Model 6 variants (as previously listed) by incorporating robust cluster standard errors. The results from these models were tabulated in Table 53 on page 243. Again, we found that Model 6 OLS and Model 6 RE +Time were the most plausible models.

At this stage, we identified the four most plausible models. We retained the Time variable to standardise the models[105]. The models were as follows:

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[104] Note that Model 6 RE +Time +$Time^2$ had the same amount of insignificant variables of interest. However, if $Time^2$ which was insignificant was removed, this model would become Model 6 RE +Time and produce the same results as the latter.

[105] As we initially believed that Time might have an influence on the costs.

- Model 6 OLS +Time
- Model 6 OLS VCE CL +Time (with robust cluster standard errors)
- Model 6 RE +Time
- Model 6 RE VCE CL +Time (with robust cluster standard errors)

Model 6 OLS +Time did not account for the panel structure. So, we set this model aside. Model 6 OLS VCE CL +Time also did not account for the panel structure, but the standard error issue was dealt with by making them cluster robust. Plus, being OLS, it had many desirable properties. Therefore, we kept this model for results comparison. Model 6 RE +Time recognised the panel structure and made specific assumptions about the error term to reflect the structure. We kept this model for results comparison.

Model 6 RE VCE CL +Time recognised the panel structure and applied robust cluster standard errors. There is debate on whether applying robust cluster standard errors on a model that had already recognised the panel structure was necessary or appropriate. Having made a specific assumption about the error term, it seems odd to try to correct the standard errors for some other form of autocorrelation/ heteroscedasticity. The counterargument would be that the random effects model partly deals with structure in the errors. However, there still could be some remaining heteroscedasticity or autocorrelation in the residuals that need to be addressed. As this debate has no clear outcome, we kept this model for results comparison.

5. The final step in the preferred model selection

We assessed the results generated by Model 6 OLS VCE CL +Time, Model 6 RE +Time, and Model 6 RE VCE CL +Time — particularly, the costs, CED, and CES by rail mode. From this, we would get a general idea of the similarities and differences in the models' results. We purged all the insignificant dummy interactions, followed by the insignificant density and scale variables (i.e., Density, $Density^2$, Network, $Network^2$). By doing so, we managed to get CED and CES graphs which were easier to explain. We then purged some other insignificant variables to make the four models more efficient.

i. Costs

Table 45 on page 217 shows the differences in costs between the over-ground, monorail, and under-ground after the purging process. The first column shows the model's name, and the second column shows whether the differences between rail modes mattered. We set the level of significance at 0.05.

Table 45. Differences in costs by rail mode (after the purging process)

Model	Cost Differences between Modes
Model 6 OLS	H0: DMO=DMM (0.0104)
VCE CL	H0: DMO=DMU (0.0000)
+Time	H0: DMM=DMU (0.0001)
Model 6 RE	H0: DMO=DMM (0.0000)
+Time	H0: DMO=DMU (0.0517)
	H0: DMM=DMU (0.0000)
Model 6 RE	H0: DMO=DMM (0.0000)
VCE CL	H0: DMO=DMU (0.3635)
+Time	H0: DMM=DMU (0.0000)

Note: Significance value in parenthesis; DMO = Over-Ground; DMM = Monorail; DMU = Under-Ground; OLS = Ordinary Least Squared; RE = Random Effects; VCE CL = Robust Cluster

Holding other factors constant, all three models agreed that the over-ground and the monorail were different in terms of how much the two affected the costs. The models also agreed that the monorail and the under-ground differed in how much the two affected the costs. Except for Model 6 OLS VCE CL +Time, they suggested that the over-ground and the under-ground were not different regarding how much the two affected the costs. However, the significance value from Model 6 RE +Time was 0.0517. It means there is weaker evidence to support that the over-ground and the under-ground were different. At 94%

confidence level, Model 6 RE +Time suggested that there was indeed a significant difference between the over-ground and the under-ground in terms of how much they affected the costs. We concluded that all models produced similar results on the operating costs of urban rail modes.

ii. CED

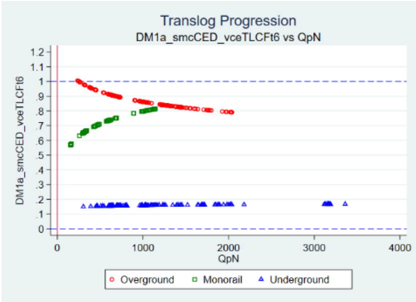
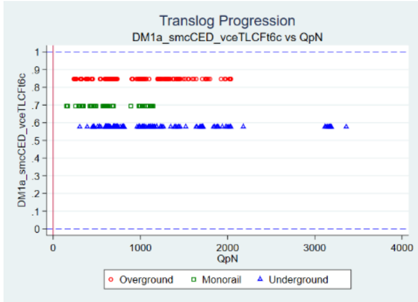
The CED graphs generated by the three models were tabulated in Table 46 on page 219. The first column shows the model's name. The second and third columns show the CED before and after purging. The fourth column shows whether the differences between rail modes mattered. We set the level of significance at 0.05.

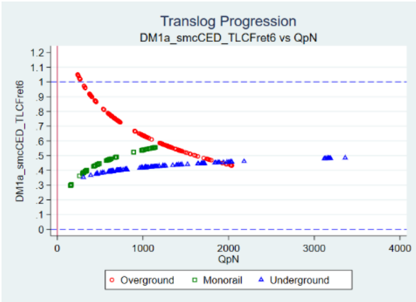
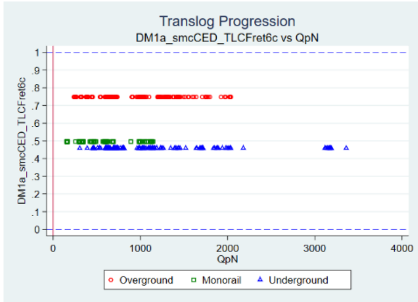
Holding other factors constant, all three models suggested that cost elasticity did not vary with Density for each rail mode. The models also suggested that for each rail mode, the costs were inelastic to density — resting between 0 and 1. The cost increment would be less than one per cent given a one per cent density increment.

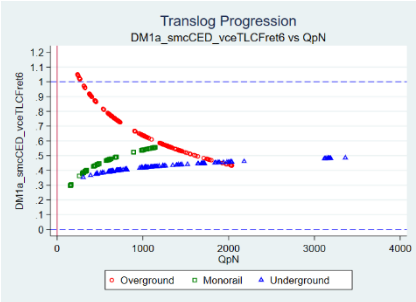
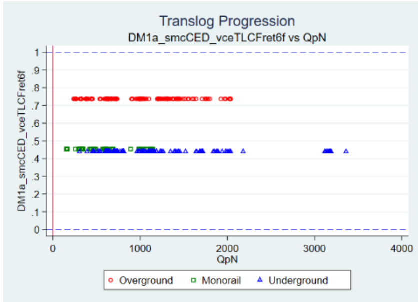
All three models showed that the under-ground had the lowest CED, followed by the monorail and the over-ground. It means that the under-ground had the least cost sensitivity towards Density, followed by the monorail and the over-ground. However, there was no significant difference between the monorail and the under-ground.

Model 6 RE VCE CL +Time suggested no significant difference (at 0.05 significance level) between the monorail and the over-ground. Even so, the significance value was 0.0651. It means there is weaker evidence to support that the over-ground and the under-ground were different. We concluded that all models produced similar results on the CED of urban rail modes.

Table 46. CED generated by the four Model 6 Variants (before and after the purging process)

Model	CED - Before Purging	CED - After Purging	Differences between Modes
Model 6 OLS **VCE CL** **+Time**	 Density[2] DMO× (0.5764) DMM× (0.2947) DMU× (0.9865)	 	H0: DMO=DMM (0.0328) H0: DMO=DMU (0.0239) H0: DMM=DMU (0.3858)

Model	**CED - Before Purging**	**CED - After Purging**	**Differences between Modes**
Model 6 RE **+Time**	 Density[2] DMO× (0.0598) DMM× (0.4879) DMU× (0.6585)		H0: DMO=DMM (0.0169) H0: DMO=DMU (0.0005) H0: DMM=DMU (0.6965)

Model	CED - Before Purging	CED - After Purging	Differences between Modes
Model 6 RE **VCE CL** **+Time**	 Density² DMO× (0.1143) DMM× (0.5899) DMU× (0.8253)		H0: DMO=DMM (0.0651) H0: DMO=DMU (0.0148) H0: DMM=DMU (0.9261)

Note: ✓ = significant at 0.05; × = insignificant at 0.05; significance value in parenthesis; DMO = Over-Ground; DMM = Monorail; DMU = Under-Ground; OLS = Ordinary Least Squared; RE = Random Effects; VCE CL = Robust Cluster.

iii. CES

The CES graphs generated by the three models were tabulated in Table 47 on page 223. The first column shows the model's name. The second and third columns show the CES before and after purging. The fourth column shows whether the differences between rail modes mattered. We set the level of significance at 0.05.

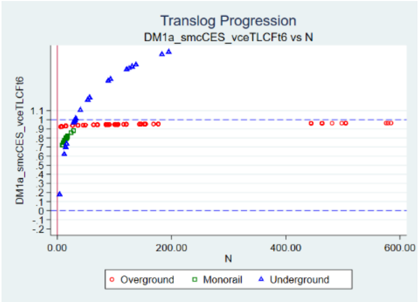
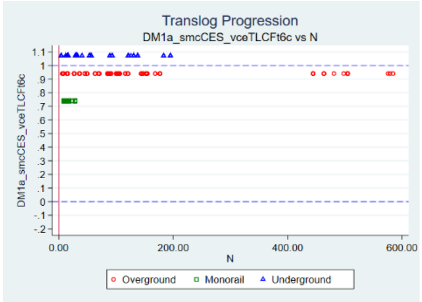
Holding other factors constant, all three models suggested that the cost elasticity did not vary with Scale for each rail mode. The models also showed that the monorail had the lowest CES, followed by the over-ground and the under-ground. It means that the monorail had the least cost sensitivity towards Scale, followed by the over-ground and the under-ground. However, they[106] suggested that the over-ground and the under-ground were not different.

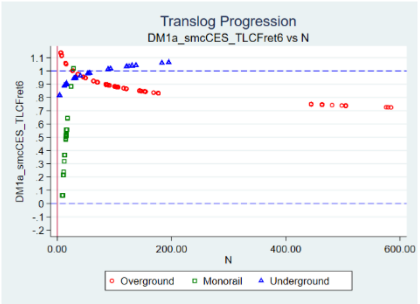
According to the models, it was difficult to determine whether the CES of the under-ground sat below, above or at the unitary line. Likewise, it was difficult to determine whether the CES of the over-ground[107] sat below, above or at the unitary line. We concluded that all models produced similar results on the CES of urban rail modes.

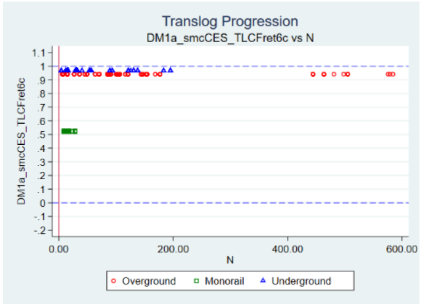
[106] The significance value from Model 6 OLS VCE CL +Time was 0.0665. This means that there is weaker evidence to support that the over-ground and the under-ground were different.

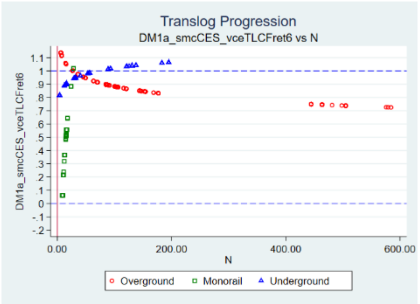
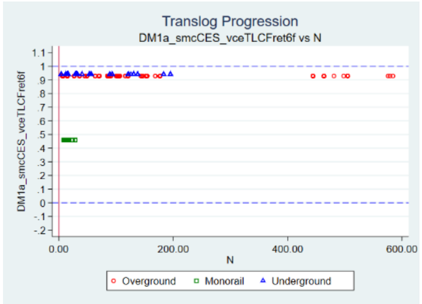
[107] The significance value from Model 6 OLS VCE CL +Time was 0.0846, and the significance value from Model 6 RE +Time was 0.0884. This means there were weaker evidence to support that the CES of the over-ground sat below the unitary line.

Table 47. CES generated by the four Model 6 Variants (before and after the purging process)

Model	CES - Before Purging	CES - After Purging	CES Differences between Modes
Model 6 **OLS** **VCE CL** **+Time**	 Network[2] DMO✗ (0.8583) DMM✗ (0.7109) DMU✗ (0.0613)		H0: DMO=DM (0.0219) H0: DMO=DMU (0.0665) H0: DMM=DMU (0.0077) H0: DMO=1 (0.0846) H0: DMU=1 (0.2481)

<table>
<tr><th>Model</th><th>CES - Before Purging</th><th>CES - After Purging</th><th>CES Differences between Modes</th></tr>
<tr>
<td>Model 6
RE
+Time</td>
<td>

Network[2]
DMO× (0.0819)
DMM× (0.0588)
DMU× (0.4394)</td>
<td>
</td>
<td>H0: DMO=DMM
(0.0004)
H0: DMO=DMU
(0.6601)
H0: DMM=DMU
(0.0004)
H0: DMO=1
(0.0884)
H0: DMU=1
(0.4776)</td>
</tr>
</table>

Model	CES - Before Purging	CES - After Purging	CES Differences between Modes
Model 6 **RE** **VCE CL** **+Time**	 Network[2] DMO✗ (0.2523) DMM✗ (0.0242) DMU✗ (0.5213)		H0: DMO=DMM (0.0009) H0: DMO=DMU (0.931) H0: DMM=DMU (0.0081) H0: DMO=1 (0.1892) H0: DMU=1 (0.6212)

Note: ✓ = significant at 0.05; ✗ = insignificant at 0.05; significance value in parenthesis; DMO = Over-Ground; DMM = Monorail; DMU = Under-Ground; OLS = Ordinary Least Squared; RE = Random Effects; VCE CL = Robust Cluster.

6. The Preferred Model

After assessing the results, we concluded that there were a lot of similarities between the three models (i.e., Model 6 OLS VCE CL +Time, Model 6 RE +Time, and Model 6 RE VCE CL +Time) concerning the costs, CED, and CES by rail mode. We prefer Model 6 RE +Time based on these rationales:

a. Although Model 6 OLS VCE CL +Time has dealt with the issue around the standard errors by making them cluster robust, an OLS initially did not account for the panel structure, and
b. There is debate on whether applying robust cluster standard errors on a model that had already recognised the panel structure was necessary or appropriate. In our case, it is Model 6 RE VCE CL +Time.

The regression results from Model 6 RE +Time (after purging) can be found in Table 49 on page 228. This model had the following insignificant variables removed for the same reasons we mentioned earlier — to get CED and CES graphs which were easier to explain and to make the model more efficient:

- mode dummy interactions with Density^2 (i.e., LnmcQpN2_DMM, LnmcQpN2_DMU),
- mode dummy interactions with Network^2 (i.e., LnmcN2_DMM, LnmcN2_DMU),
- Density^2 (i.e., LnmcQpN2),
- Network^2 (i.e., LnmcN2),
- the interaction between Density and Energy Price, and
- the interaction between Density and Labour Price.

This model has mode-specific intercepts, which allowed us to evaluate whether there is a difference in operating costs between modes. It also has mode interaction terms with density and scale, allowing us to evaluate whether elasticities vary by mode.

Table 48. Rich Model (Model 12) Regression Results

```
Linear regression                               Number of obs     =        552
                                                F(44, 507)        =    4057.33
                                                Prob > F          =     0.0000
                                                R-squared         =     0.9923
                                                Root MSE          =     .12563
```

LnmcCELMpmcPM	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
LnmcQpN	.8679517	.0276823	31.35	0.000	.8135655	.9223379
LnmcQpN_DMM	-.5295453	.3514693	-1.51	0.133	-1.220061	.1609703
LnmcQpN_DMU	-.5209305	.0676858	-7.70	0.000	-.6539096	-.3879514
LnmcPEpmcPM	.1749749	.0507289	3.45	0.001	.0753101	.2746397
LnmcPEpmcPM_DMM	.0112513	.2631861	0.04	0.966	-.5058184	.5283209
LnmcPEpmcPM_DMU	-.1389436	.0706914	-1.97	0.050	-.2778278	-.0000594
LnmcPLpmcPM	.5590998	.0537577	10.40	0.000	.4534844	.6647151
LnmcPLpmcPM_DMM	.8727431	.3819692	2.28	0.023	.1223056	1.62318
LnmcPLpmcPM_DMU	.5022302	.1010878	4.97	0.000	.3036275	.7008328
LnmcPMpmcPM	0	(omitted)				
LnmcPMpmcPM_DMM	0	(omitted)				
LnmcPMpmcPM_DMU	0	(omitted)				
LnmcN	.9979434	.0207715	48.04	0.000	.9571346	1.038752
LnmcN_DMM	-.405528	.1891383	-2.14	0.033	-.7771193	-.0339367
LnmcN_DMU	.251056	.054238	4.63	0.000	.144497	.357615
halfLnmcQpN2	-.3903217	.0637067	-6.13	0.000	-.5154835	-.26516
halfLnmcQpN2_DMM	.5081545	.0834349	6.09	0.000	.3442338	.6720752
halfLnmcQpN2_DMU	.6806861	.1856934	3.67	0.000	.3158629	1.045509
halfLnmcN2	-.0379035	.0148741	-2.55	0.011	-.0671259	-.0086811
halfLnmcN2_DMM	.1162777	.1531928	0.76	0.448	-.1846932	.4172485
halfLnmcN2_DMU	.3189083	.0863441	3.69	0.000	.149272	.4885447
LnmcQpNLnmcPEpmcPM	-.3746172	.1029367	-3.64	0.000	-.5768522	-.1723822
LnmcQpNLnmcPEpmcPM_DMM	.3578783	.1210049	2.96	0.003	.1201454	.5956111
LnmcQpNLnmcPEpmcPM_DMU	.6723351	.1434172	4.69	0.000	.39057	.9541002
LnmcQpNLnmcPLpmcPM	.1153414	.0884571	1.30	0.193	-.0584462	.2891291
LnmcQpNLnmcPLpmcPM_DMM	-.1503834	.1214983	-1.24	0.216	-.3890856	.0883187
LnmcQpNLnmcPLpmcPM_DMU	-.5485846	.125344	-4.38	0.000	-.7948422	-.3023271
LnmcQpNLnmcPMpmcPM	0	(omitted)				
LnmcQpNLnmcPMpmcPM_DMM	0	(omitted)				
LnmcQpNLnmcPMpmcPM_DMU	0	(omitted)				
LnmcQpNLnmcN	-.1529072	.2171818	-0.70	0.482	-.5795943	.27378
LnmcQpNLnmcN_DMM	.2351482	.2178923	1.08	0.281	-.1929348	.6632311
LnmcQpNLnmcN_DMU	.4157494	.2203618	1.89	0.060	-.0171853	.8486841
LnmcPEpmcPMLnmcPLpmcPM	1.345903	.2987936	4.50	0.000	.7588773	1.93293
LnmcPEpmcPMLnmcPLpmcPM_~M	-1.136497	.3130307	-3.63	0.000	-1.751494	-.5215003
LnmcPEpmcPMLnmcPLpmcPM_~U	-.7512665	.3599294	-2.09	0.037	-1.458403	-.0441297
LnmcPEpmcPMLnmcPMpmcPM	0	(omitted)				
LnmcPEpmcPMLnmcPMpmcPM_~M	0	(omitted)				
LnmcPEpmcPMLnmcPMpmcPM_~U	0	(omitted)				
LnmcPLpmcPMLnmcPMpmcPM	0	(omitted)				
LnmcPLpmcPMLnmcPMpmcPM_~M	0	(omitted)				
LnmcPLpmcPMLnmcPMpmcPM_~U	0	(omitted)				
halfLnmcPEpmcPM2	-1.366104	.3009921	-4.54	0.000	-1.95745	-.7747589
halfLnmcPEpmcPM2_DMM	.9586583	.3364032	2.85	0.005	.2977423	1.619574
halfLnmcPEpmcPM2_DMU	1.139359	.3379774	3.37	0.001	.4753508	1.803368
halfLnmcPLpmcPM2	-.9289805	.3078603	-3.02	0.003	-1.53382	-.3241415
halfLnmcPLpmcPM2_DMM	1.164523	.3303412	3.53	0.000	.5155165	1.813529
halfLnmcPLpmcPM2_DMU	-.4087443	.4051334	-1.01	0.313	-1.204691	.3872026
halfLnmcPMpmcPM2	0	(omitted)				
halfLnmcPMpmcPM2_DMM	0	(omitted)				
halfLnmcPMpmcPM2_DMU	0	(omitted)				
LnmcNLnmcPEpmcPM	-.1984942	.052118	-3.81	0.000	-.300888	-.0961004
LnmcNLnmcPEpmcPM_DMM	.2569492	.1709594	1.50	0.133	-.0789269	.5928253
LnmcNLnmcPEpmcPM_DMU	.0901063	.080791	1.12	0.265	-.0686201	.2488327
LnmcNLnmcPLpmcPM	.1342877	.0538261	2.49	0.013	.0285379	.2400374
LnmcNLnmcPLpmcPM_DMM	.4638742	.2470062	1.88	0.061	-.0214074	.9491559
LnmcNLnmcPLpmcPM_DMU	.2472222	.0776517	3.18	0.002	.0946635	.399781
LnmcNLnmcPMpmcPM	0	(omitted)				
LnmcNLnmcPMpmcPM_DMM	0	(omitted)				
LnmcNLnmcPMpmcPM_DMU	0	(omitted)				
DMM	-.8019417	.2181529	-3.68	0.000	-1.230537	-.3733467
DMU	.1030802	.0333156	3.09	0.002	.0376266	.1685338
_cons	.0382716	.018366	2.08	0.038	.0021887	.0743545

Note: Refer to Table 51 on page 230 for Regression Term Descriptions.

Table 49. Model 6 RE +Time Regression Results (after purging)

```
Random-effects GLS regression                   Number of obs     =        552
Group variable: id                              Number of groups  =         46

R-sq:                                           Obs per group:
     within  = 0.7413                                         min =         12
     between = 0.9742                                         avg =       12.0
     overall = 0.9728                                         max =         12

                                                Wald chi2(17)     =    3493.55
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000
```

LnmcCELMpmcPM	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Time	-.0064877	.0010459	-6.20	0.000	-.0085375	-.0044378
LnmcQpN	.7490696	.056358	13.29	0.000	.63861	.8595292
LnmcQpN_DMM	-.2523734	.1056724	-2.39	0.017	-.4594874	-.0452593
LnmcQpN_DMU	-.290507	.0832885	-3.49	0.000	-.4537494	-.1272646
LnmcPEpmcPM	.1612759	.0217122	7.43	0.000	.1187208	.2038311
LnmcPLpmcPM	.4950746	.0255158	19.40	0.000	.4450645	.5450847
LnmcPMpmcPM	0	(omitted)				
LnmcN	.9430847	.0333984	28.24	0.000	.877625	1.008544
LnmcN_DMM	-.4184442	.1186433	-3.53	0.000	-.6509807	-.1859076
LnmcN_DMU	.0251065	.0570915	0.44	0.660	-.0867907	.1370037
LnmcQpNLnmcN	.1300572	.0354513	3.67	0.000	.0605739	.1995404
LnmcPEpmcPMLnmcPLpmcPM	.2360141	.0463818	5.09	0.000	.1451076	.3269207
LnmcPEpmcPMLnmcPMpmcPM	0	(omitted)				
LnmcPLpmcPMLnmcPMpmcPM	0	(omitted)				
halfLnmcPEpmcPM2	-.1945434	.050584	-3.85	0.000	-.2936861	-.0954007
halfLnmcPLpmcPM2	-.1243123	.0522893	-2.38	0.017	-.2267975	-.0218272
halfLnmcPMpmcPM2	0	(omitted)				
LnmcNLnmcPEpmcPM	-.0386899	.0123049	-3.14	0.002	-.062807	-.0145729
LnmcNLnmcPLpmcPM	.1233431	.0149579	8.25	0.000	.0940262	.15266
LnmcNLnmcPMpmcPM	0	(omitted)				
DMM	-.9584722	.2188037	-4.38	0.000	-1.38732	-.5296249
DMU	.1475098	.0758003	1.95	0.052	-.0010561	.2960757
_cons	.0073412	.0434008	0.17	0.866	-.0777228	.0924053
sigma_u	.16828347					
sigma_e	.04938309					
rho	.92071368	(fraction of variance due to u_i)				

Note: Refer to Table 51 on page 230 for Regression Term Descriptions.

Table 50. Model 6 Regression Results

Linear regression			
	Number of obs	=	552
	F(24, 527)	=	4270.81
	Prob > F	=	0.0000
	R-squared	=	0.9889
	Root MSE	=	.14768

LnmcCELMpmcPM	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
LnmcQpN	.8677457	.0320383	27.08	0.000	.8048072	.9306841
LnmcQpN_DMM	-.1010176	.0606048	-1.67	0.096	-.2200742	.018039
LnmcQpN_DMU	-.709582	.0603205	-11.76	0.000	-.8280802	-.5910838
LnmcPEpmcPM	.1261999	.0313899	4.02	0.000	.0645352	.1878647
LnmcPLpmcPM	.7673988	.0478156	16.05	0.000	.6734662	.8613314
LnmcPMpmcPM	0	(omitted)				
LnmcN	.9473041	.0161512	58.65	0.000	.9155754	.9790328
LnmcN_DMM	.0819879	.2792852	0.29	0.769	-.4666611	.6306369
LnmcN_DMU	.4641166	.0486684	9.54	0.000	.3685088	.5597244
halfLnmcQpN2	-.0968506	.0604202	-1.60	0.110	-.2155447	.0218434
halfLnmcQpN2_DMM	.1952834	.0929878	2.10	0.036	.012611	.3779557
halfLnmcQpN2_DMU	.0866719	.1638975	0.53	0.597	-.2353008	.4086445
halfLnmcN2	.0097808	.0158279	0.62	0.537	-.0213127	.0408744
halfLnmcN2_DMM	.1252692	.1652301	0.76	0.449	-.1993212	.4498597
halfLnmcN2_DMU	.4006415	.0798579	5.02	0.000	.2437627	.5575203
LnmcQpNLnmcPEpmcPM	.1031442	.0411747	2.51	0.013	.0222575	.1840309
LnmcQpNLnmcPLpmcPM	-.2021377	.0509691	-3.97	0.000	-.3022652	-.1020101
LnmcQpNLnmcPMpmcPM	0	(omitted)				
LnmcQpNLnmcN	.1374142	.014393	9.55	0.000	.1091396	.1656888
LnmcPEpmcPMLnmcPLpmcPM	.1861573	.09764	1.91	0.057	-.005654	.3779687
LnmcPEpmcPMLnmcPMpmcPM	0	(omitted)				
LnmcPLpmcPMLnmcPMpmcPM	0	(omitted)				
halfLnmcPEpmcPM2	-.1785228	.0647755	-2.76	0.006	-.3057726	-.051273
halfLnmcPLpmcPM2	-.4794991	.1187498	-4.04	0.000	-.7127802	-.2462181
halfLnmcPMpmcPM2	0	(omitted)				
LnmcNLnmcPEpmcPM	.0146542	.0250037	0.59	0.558	-.0344649	.0637733
LnmcNLnmcPLpmcPM	.119271	.0305815	3.90	0.000	.0591944	.1793476
LnmcNLnmcPMpmcPM	0	(omitted)				
DMM	-.0946823	.2371826	-0.40	0.690	-.5606217	.3712572
DMU	.2186959	.02183	10.02	0.000	.1758114	.2615804
_cons	-.0121786	.0177136	-0.69	0.492	-.0469767	.0226194

Note: Refer to Table 51 on page 230 for Regression Term Descriptions.

Table 51. Regression Term Descriptions

Term	*Description*
LnmcCELMpmcPM	Operating Costs
Time	Period
LnmcQpN	Traffic Density
LnmcQpN_DMM	Monorail-Traffic Density Interaction
LnmcQpN_DMU	Underground-Traffic Density Interaction
LnmcPEpmcPM	Energy Price
LnmcPEpmcPM_DMM	Monorail-Energy Price Interaction
LnmcPEpmcPM_DMU	Underground-Energy Price Interaction
LnmcPLpmcPM	Labour Price
LnmcPLpmcPM_DMM	Monorail-Labour Price Interaction
LnmcPLpmcPM_DMU	Underground-Labour Price Interaction
LnmcPMpmcPM	Material Price
LnmcPMpmcPM_DMM	Monorail-Material Price Interaction
LnmcPMpmcPM_DMU	Underground-Material Price Interaction
LnmcN	Network Length
LnmcN_DMM	Monorail-Network Length Interaction
LnmcN_DMU	Underground-Network Length Interaction
halfLnmcQpN2	Traffic Density Squared
halfLnmcQpN2_DMM	Monorail-Traffic Density Squared Interaction
halfLnmcQpN2_DMU	Underground-Traffic Density Squared Interaction
halfLnmcN2	Network Length Squared

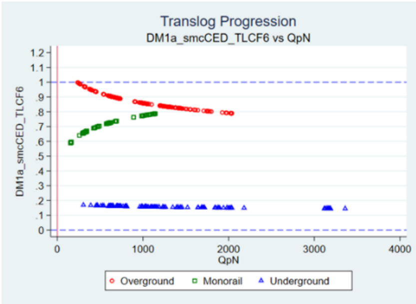
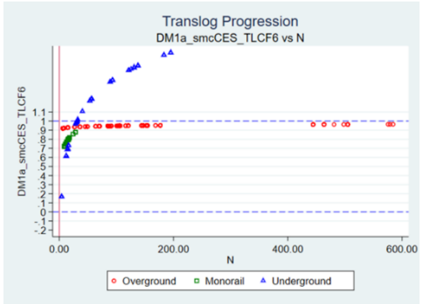
Term	*Description*
halfLnmcN2_DMM	Monorail-Network Length Squared Interaction
halfLnmcN2_DMU	Underground-Network Length Squared Interaction
LnmcQpNLnmcPEpmcPM	Traffic Density-Energy Price Interaction
LnmcQpNLnmcPEpmcPM_DMM	Monorail-Traffic Density-Energy Price Interaction
LnmcQpNLnmcPEpmcPM_DMU	Underground-Traffic Density-Energy Price Interaction
LnmcQpNLnmcPLpmcPM	Traffic Density-Labour Price Interaction
LnmcQpNLnmcPLpmcPM_DMM	Monorail-Traffic Density-Labour Price Interaction
LnmcQpNLnmcPLpmcPM_DMU	Underground-Traffic Density-Labour Price Interaction
LnmcQpNLnmcPMpmcPM	Traffic Density-Material Price Interaction
LnmcQpNLnmcPMpmcPM_DMM	Monorail-Traffic Density-Material Price Interaction
LnmcQpNLnmcPMpmcPM_DMU	Underground-Traffic Density-Material Price Interaction
LnmcQpNLnmcN	Traffic Density-Network Length Interaction
LnmcQpNLnmcN_DMM	Monorail-Traffic Density-Network Length Interaction
LnmcQpNLnmcN_DMU	Underground-Traffic Density-Network Length Interaction
LnmcPEpmcPMLnmcPLpmcPM	Energy Price-Labour Price Interaction
LnmcPEpmcPMLnmcPLpmcPM_DMM	Monorail-Energy Price-Labour Price Interaction

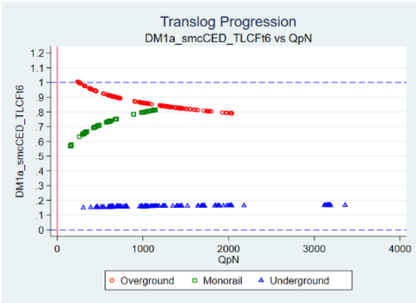
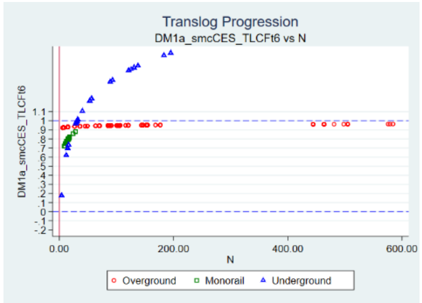
Term	*Description*
LnmcPEpmcPMLnmcPLpmcPM_DMU	Underground-Energy Price-Labour Price Interaction
LnmcPEpmcPMLnmcPMpmcPM	Energy Price-Material Price Interaction
LnmcPEpmcPMLnmcPMpmcPM_DMM	Monorail-Energy Price-Material Price Interaction
LnmcPEpmcPMLnmcPMpmcPM_DMU	Underground-Energy Price-Material Price Interaction
LnmcPLpmcPMLnmcPMpmcPM	Labour Price-Material Price Interaction
LnmcPLpmcPMLnmcPMpmcPM_DMM	Monorail-Labour Price-Material Price Interaction
LnmcPLpmcPMLnmcPMpmcPM_DMU	Underground-Labour Price-Material Price Interaction
halfLnmcPEpmcPM2	Energy Price Squared
halfLnmcPEpmcPM2_DMM	Monorail-Energy Price Squared Interaction
halfLnmcPEpmcPM2_DMU	Underground-Energy Price Squared Interaction
halfLnmcPLpmcPM2	Labour Price Squared
halfLnmcPLpmcPM2_DMM	Monorail-Labour Price Squared Interaction
halfLnmcPLpmcPM2_DMU	Underground-Labour Price Squared Interaction
halfLnmcPMpmcPM2	Material Price Squared
halfLnmcPMpmcPM2_DMM	Monorail-Material Price Squared Interaction
halfLnmcPMpmcPM2_DMU	Underground-Material Price Squared Interaction
LnmcNLnmcPEpmcPM	Network Length-Energy Price Interaction
LnmcNLnmcPEpmcPM_DMM	Monorail-Network Length-Energy Price Interaction

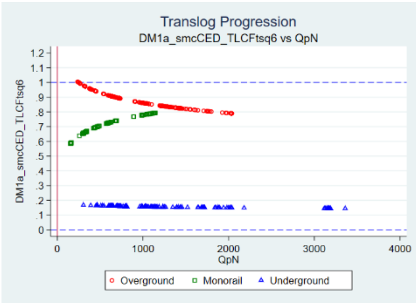
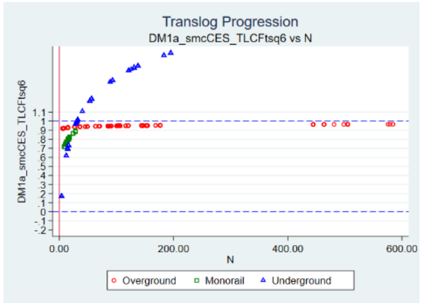
Term	*Description*
LnmcNLnmcPEpmcPM_DMU	Underground-Network Length-Energy Price Interaction
LnmcNLnmcPLpmcPM	Network Length-Labour Price Interaction
LnmcNLnmcPLpmcPM_DMM	Monorail-Network Length-Labour Price Interaction
LnmcNLnmcPLpmcPM_DMU	Underground-Network Length-Labour Price Interaction
LnmcNLnmcPMpmcPM	Network Length-Material Price Interaction
LnmcNLnmcPMpmcPM_DMM	Monorail-Network Length-Material Price Interaction
LnmcNLnmcPMpmcPM_DMU	Underground-Network Length-Material Price Interaction
DMM	Monorail Mode
DMU	Underground Mode

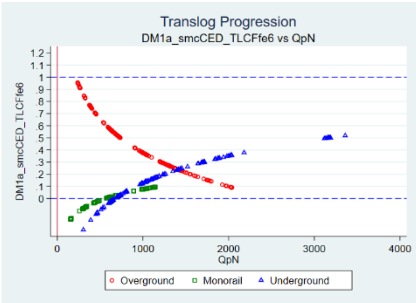
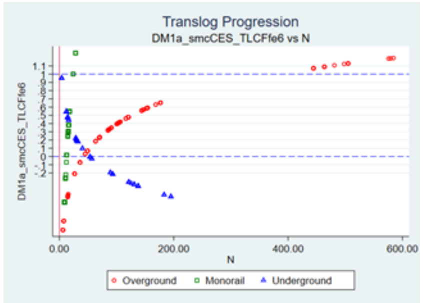
Note: Refer to Chapter 4 for more details on the variables.

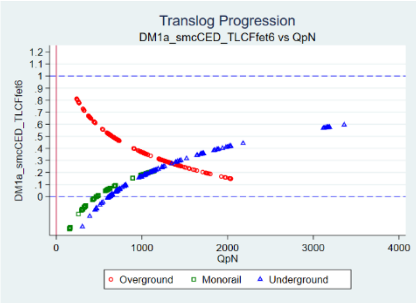
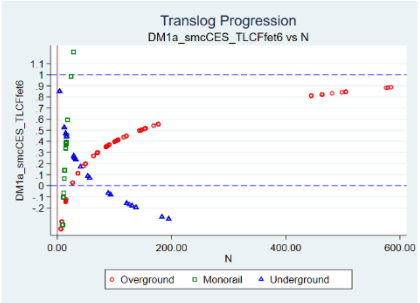
Table 52. CED and CES generated by several Model 6 variants.

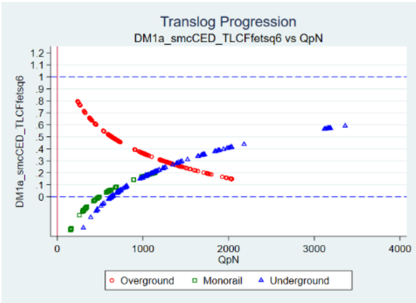
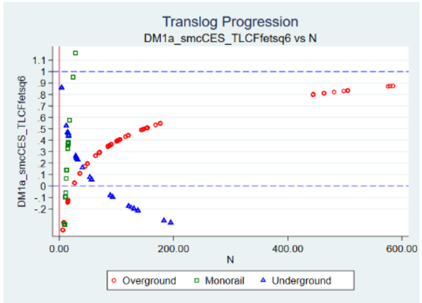
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 OLS	 **Intuitive** findings on CED (convexity in DMO and DMU was insignificant)	Density DMO✓ DMM✓ DMU✓ Density^2 DMO✗ DMM✗ DMU✗	 **Intuitive** findings on CES	Network DMO✓ DMM✓ DMU✓ Network^2 DMO✗ DMM✗ DMU✓	Not Applicable

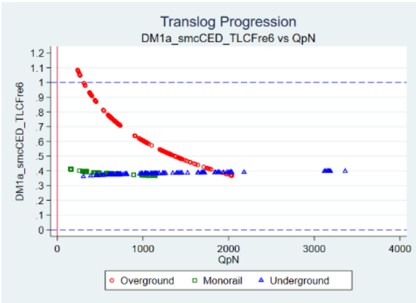
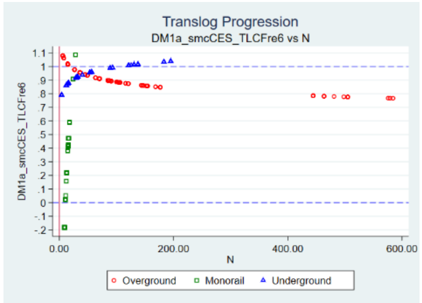
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 OLS +Time	 **Intuitive** findings on CED (convexity in DMO and DMU was insignificant)	Density DMO✓ DMM✓ DMU✓ Density^2 DMO✗ DMM✗ DMU✗	 **Intuitive** findings on CES	Network DMO✓ DMM✓ DMU✓ Network^2 DMO✗ DMM✗ DMU✓	Time✗

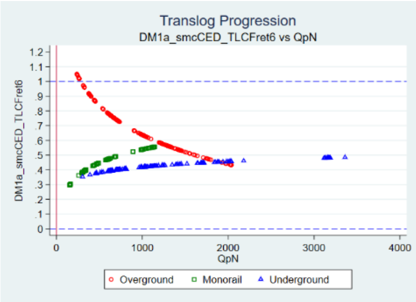
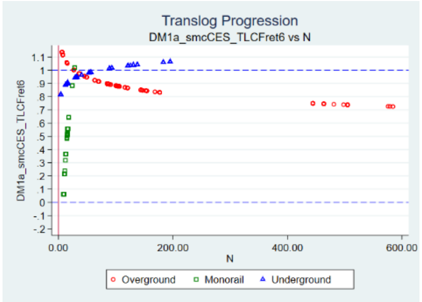
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 OLS +Time +Time2	 **Intuitive** findings on CED (convexity in DMO and DMU was insignificant)	Density DMO✓ DMM✓ DMU✓ Density^2 DMO✗ DMM✗ DMU✗	 **Intuitive** findings on CES	Network DMO✓ DMM✓ DMU✓ Network^2 DMO✗ DMM✗ DMU✓	Time✗ Time^2✗

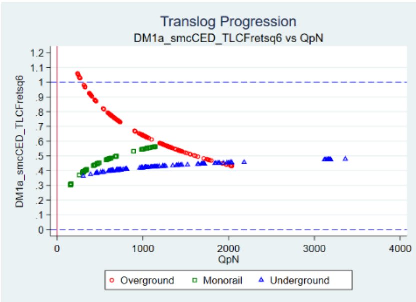
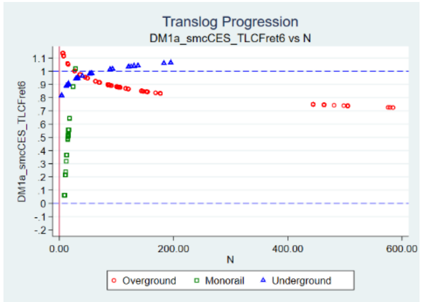
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 FE	 **Non-Intuitive** findings on CED (convexity in DMO was significant; curvature for DMU, which had some negative values, was significant)	Density DMO✓ DMM✗ DMU✗ Density^2 DMO✓ DMM✗ DMU✓	 **Non-**Intuitive findings on CES (convexity in DMU was significant; curvature for all modes which had significant negative values were significant)	Network DMO✓ DMM✓ DMU✗ Network^2 DMO✓ DMM✓ DMU✓	Not Applicable

Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 FE +Time	 **Non-Intuitive** findings on CED (curvature for DMU, which had some negative values, was significant)	Density DMO✓ DMM× DMU× Density^2 DMO× DMM× DMU✓	 **Non-Intuitive** findings on CES (convexity in DMU was significant; curvature for DMM and DMU, which had significant negative values, were significant)	Network DMO✓ DMM✓ DMU× Network^2 DMO× DMM✓ DMU✓	Time✓

Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 FE +Time +Time2	 **Non-Intuitive** findings on CED (curvature for DMU, which had some negative values, was significant)	Density DMO✓ DMM✗ DMU✗ Density^2 DMO✗ DMM✗ DMU✓	 **Non-Intuitive** findings on CES (convexity in DMU was significant; curvature for DMM and DMU, which had significant negative values, were significant)	Network DMO✓ DMM✓ DMU✗ Network^2 DMO✗ DMM✓ DMU✓	Time✗ Time^2✗

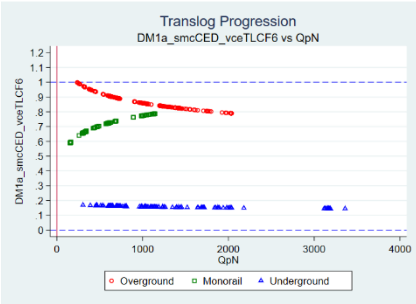
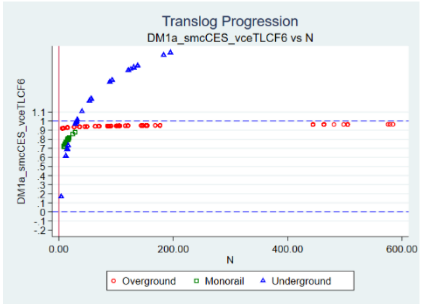
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 RE	 **Non-Intuitive** findings on CED (convexity in DMO was significant; curvature for DMO, which started with values above unitary, was significant)	Density DMO✓ DMM✓ DMU✓ Density^2 DMO✓ DMM× DMU×	 **Intuitive** findings on CES (curvature for all modes — one of which started with values above unitary — was insignificant)	Network DMO✓ DMM✓ DMU✓ Network^2 DMO× DMM✓ DMU×	Not Applicable

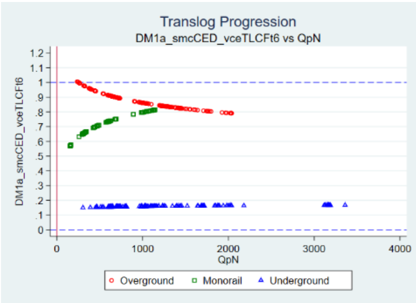
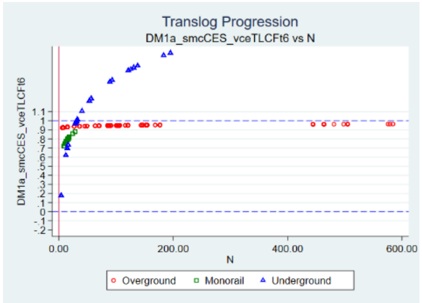
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 RE +Time	 **Intuitive** findings on CED (convexity in DMO was insignificant; curvature for DMO, which started with values above unitary, was insignificant)	Density DMO✓ DMM✓ DMU✓ Density^2 DMO× DMM× DMU×	 **Intuitive** findings on CES (curvature for all modes — one of which started with values above unitary — was insignificant)	Network DMO✓ DMM✓ DMU✓ Network^2 DMO× DMM× DMU×	Time✓

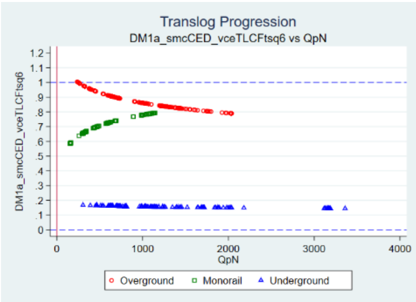
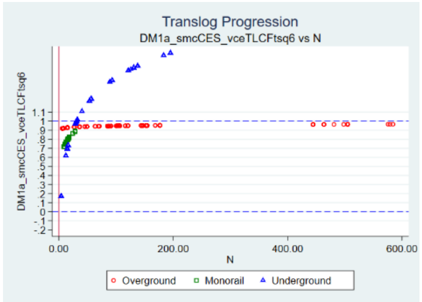
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 RE +Time +Time2	 **Intuitive** findings on CED (convexity in DMO was insignificant; curvature for DMO, which started with values above unitary, was insignificant)	Density DMO✓ DMM✓ DMU✓ Density^2 DMO× DMM× DMU×	 **Intuitive** findings on CES (curvature for all modes — one of which started with values above unitary — was insignificant)	Network DMO✓ DMM✓ DMU✓ Network^2 DMO× DMM✓ DMU×	Time✓ Time^2×

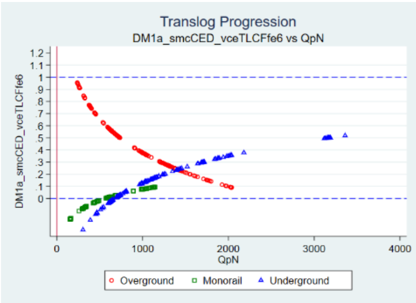
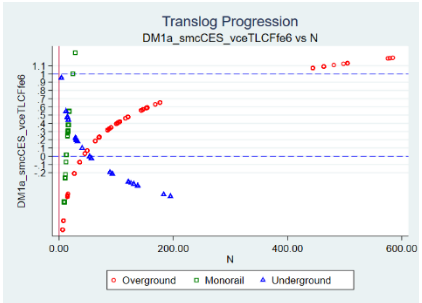
Note: ✓ Significant at 0.05 level × Insignificant at 0.05 level

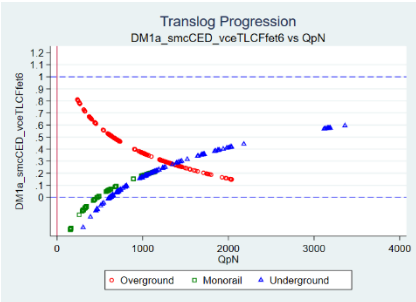
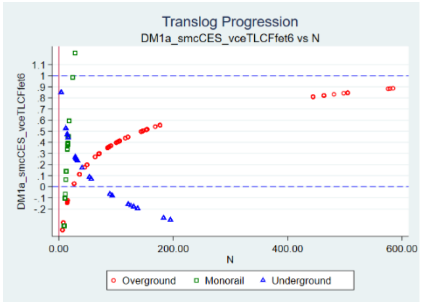
Table 53. CED and CES generated by several Model 6 variants (incorporating the robust cluster standard errors)

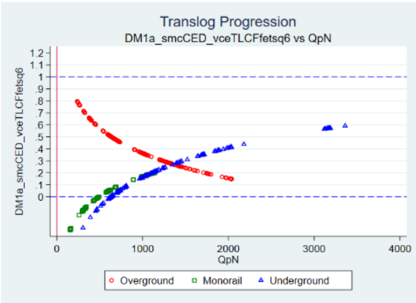
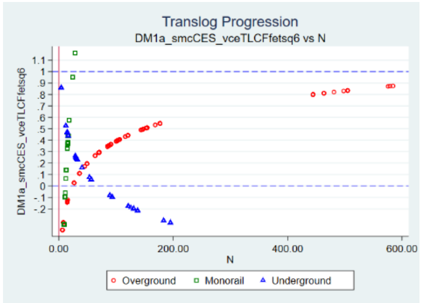
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 OLS	 **Intuitive** findings on CED (convexity in DMO and DMU was insignificant)	Density DMO✓ DMM✓ DMU× Density^2 DMO× DMM× DMU×	 **Intuitive** findings on CES	Network DMO✓ DMM× DMU✓ Network^2 DMO× DMM× DMU×	Not Applicable

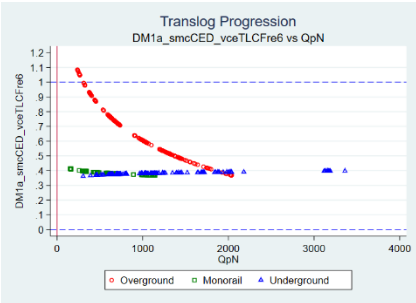
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 OLS +Time	 **Intuitive** findings on CED (convexity in DMO and DMU was insignificant)	Density DMO✓ DMM✓ DMU× Density^2 DMO× DMM× DMU×	 **Intuitive** findings on CES	Network DMO✓ DMM× DMU✓ Network^2 DMO× DMM× DMU×	Time×

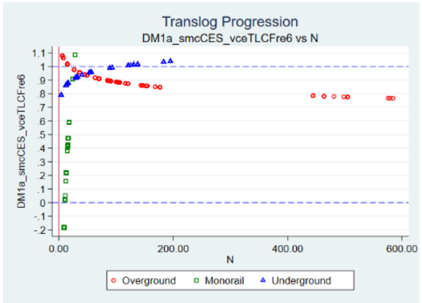
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 OLS +Time +Time2	 **Intuitive** findings on CED (convexity in DMO and DMU was insignificant)	Density DMO✓ DMM✓ DMU× Density^2 DMO× DMM× DMU×	 **Intuitive** findings on CES	Network DMO✓ DMM× DMU✓ Network^2 DMO× DMM× DMU×	Time× Time^2×

Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 FE	 **Non-Intuitive** findings on CED (curvature for DMU, which had some negative values, was significant)	Density DMO✓ DMM× DMU× Density^2 DMO× DMM× DMU✓	 **Non-Intuitive** findings on CES (convexity in DMU was significant; curvature for DMM and DMU, which had significant negative values, were significant)	Network DMO✓ DMM✓ DMU× Network^2 DMO× DMM✓ DMU✓	Not Applicable

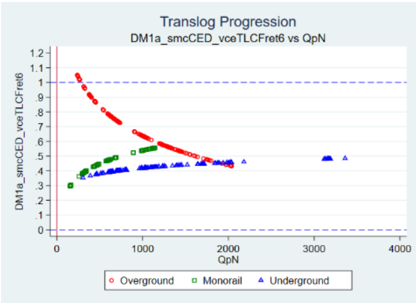
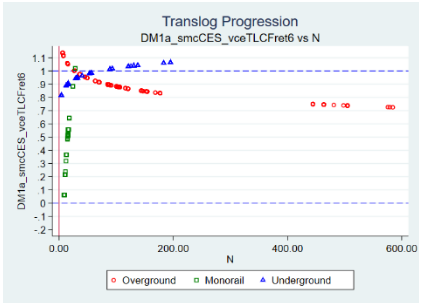
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 FE +Time	 **Non-Intuitive** findings on CED (curvature for DMU, which had some negative values, was significant)	Density DMO✓ DMM× DMU× Density^2 DMO× DMM× DMU✓	 **Non-Intuitive** findings on CES (convexity in DMU was significant; curvature for DMM and DMU, which had significant negative values, were significant)	Network DMO✓ DMM✓ DMU× Network^2 DMO× DMM✓ DMU✓	Time×

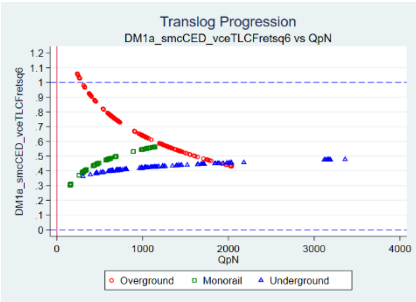
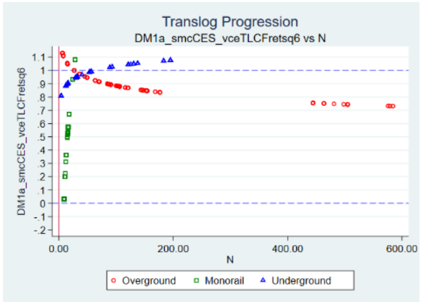
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 FE +Time +Time2	 **Non-Intuitive** findings on CED (curvature for DMU, which had some negative values, was significant)	Density DMO✓ DMM× DMU× Density^2 DMO× DMM× DMU✓	 **Non-Intuitive** findings on CES (convexity in DMU was significant; curvature for DMM and DMU, which had significant negative values, were significant)	Network DMO✓ DMM✓ DMU× Network^2 DMO× DMM✓ DMU✓	Time× Time^2×

<table>
<tr><th rowspan="2">Model</th><th colspan="2">CED</th><th colspan="2">CES</th><th>Time Variable</th></tr>
<tr><th>Graph</th><th>Significance</th><th>Graph</th><th>Significance</th><th>Significance</th></tr>
<tr><td>Model 6
RE</td><td>

Intuitive findings on CED (convexity in DMO was insignificant; curvature for DMO, which started with values above unitary, was insignificant)</td><td>Density
DMO✓
DMM×
DMU✓
Density^2
DMO×
DMM×
DMU×</td><td>

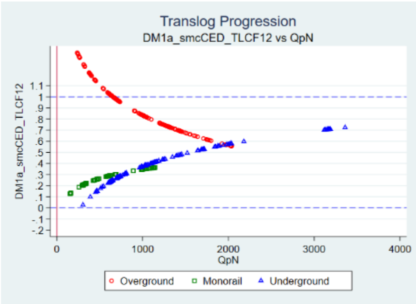
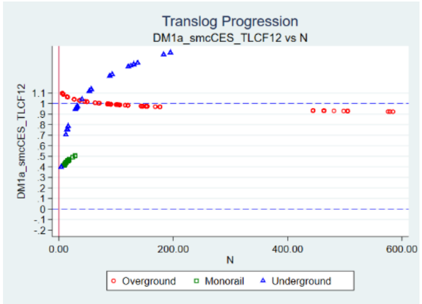
Intuitive findings on CES (curvature for all modes — one of which started with values above unitary — was insignificant)</td><td>Network
DMO✓
DMM✓
DMU✓
Network^2
DMO×
DMM✓
DMU×</td><td>Not Applicable</td></tr>
</table>

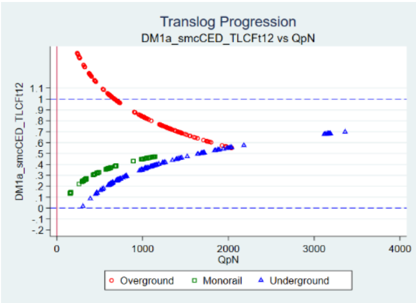
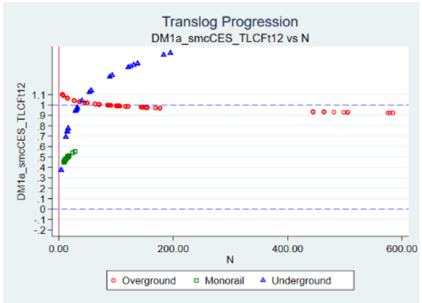
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 RE +Time	 **Intuitive** findings on CED (convexity in DMO was insignificant; curvature for DMO, which started with values above unitary, was insignificant)	Density DMO✓ DMM✓ DMU✓ Density^2 DMO✗ DMM✗ DMU✗	 **Intuitive** findings on CES (curvature for DMU, which also started with values above unitary was insignificant; curvature for DMM became significant)	Network DMO✓ DMM✓ DMU✓ Network^2 DMO✗ DMM✓ DMU✗	Time✓

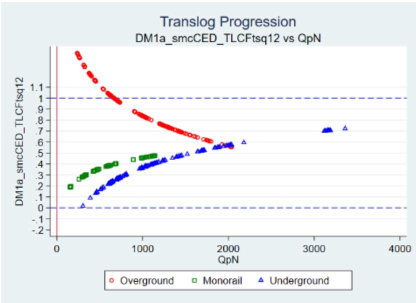
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 RE +Time +Time2	 **Intuitive** findings on CED (convexity in DMO was insignificant; curvature for DMO, which started with values above unitary, was insignificant)	Density DMO✓ DMM✓ DMU✓ Density^2 DMO× DMM× DMU×	 **Intuitive** findings on CES (curvature for all modes — one of which started with values above unitary — was insignificant)	Network DMO✓ DMM✓ DMU✓ Network^2 DMO× DMM✓ DMU×	Time✓ Time^2×

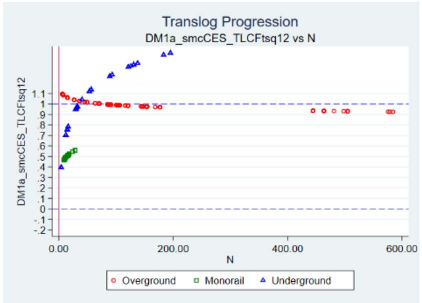
Note: ✓ = Significant at 0.05 level, × = Insignificant at 0.05 level, ✓ or × = change after the application of robust cluster errors

Table 54. CED and CES generated by several Model 12 variants.

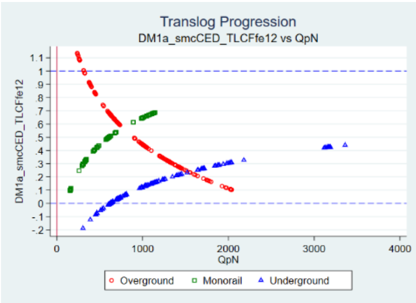
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 12	 **Non-Intuitive** findings on CED (convexity and starting values above the unitary line for DMO were significant)	Density DMO✓ DMM× DMU✓ Density^2 DMO✓ DMM✓ DMU×	 **Non-Intuitive** findings on CES (convexity and starting values above the unitary line for DMO were significant)	Network DMO✓ DMM✓ DMU✓ Network^2 DMO✓ DMM× DMU✓	Not Applicable

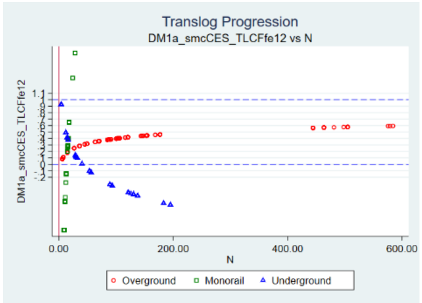
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 12 +Time	 **Non-Intuitive** findings on CED (convexity and starting values above the unitary line for DMO were significant)	Density DMO✓ DMM× DMU✓ Density^2 DMO✓ DMM✓ DMU×	 **Non-Intuitive** findings on CES (convexity and starting values above the unitary line for DMO were significant)	Network DMO✓ DMM✓ DMU✓ Network^2 DMO✓ DMM× DMU✓	Time×

<table>
<tr><th>Model</th><th colspan="2">CED</th><th colspan="2">CES</th><th>Time Variable</th></tr>
<tr><th></th><th>Graph</th><th>Significance</th><th>Graph</th><th>Significance</th><th>Significance</th></tr>
<tr>
<td>Model 12
+Time
+Time2</td>
<td>

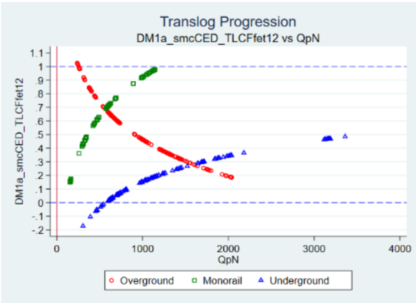
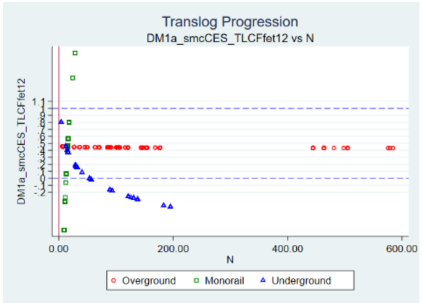
Non-Intuitive findings on CED (convexity and starting values above the unitary line for DMO were significant)</td>
<td>Density
DMO✓
DMM✗
DMU✓
Density^2
DMO✓
DMM✓
DMU✗</td>
<td>

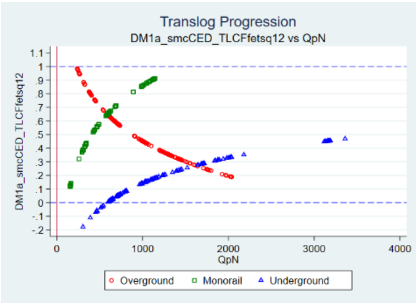
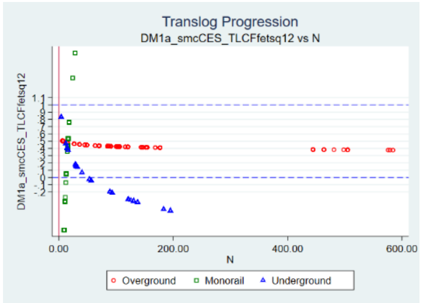
Non-Intuitive findings on CES (convexity and starting values above the unitary line for DMO were significant)</td>
<td>Network
DMO✓
DMM✓
DMU✓
Network^2
DMO✓
DMM✗
DMU✓</td>
<td>Time✗
Time^2✗</td>
</tr>
</table>

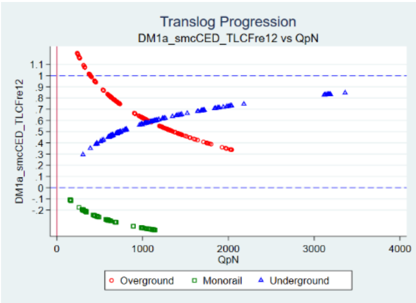
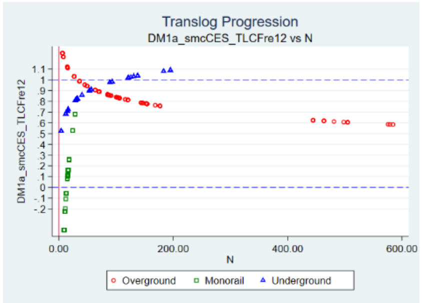
<table>
<tr><td rowspan="2">Model</td><td colspan="2">CED</td><td colspan="2">CES</td><td>Time Variable</td></tr>
<tr><td>Graph</td><td>Significance</td><td>Graph</td><td>Significance</td><td>Significance</td></tr>
<tr><td>Model 12 FE</td><td>

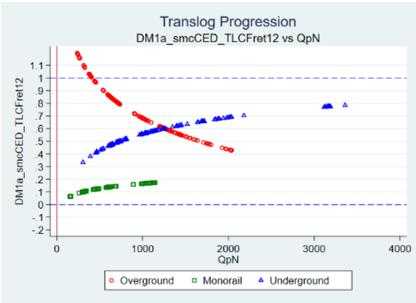
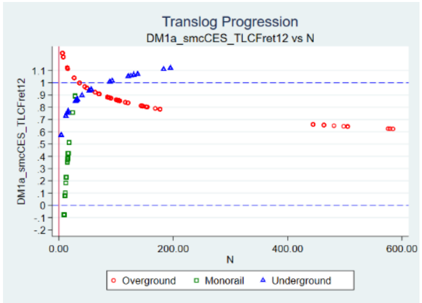
Non-Intuitive findings on CED (convexity and starting values above the unitary line for DMO were significant)</td><td>Density
DMO✓
DMM×
DMU×
$Density^2$
DMO✓
DMM×
DMU×</td><td>

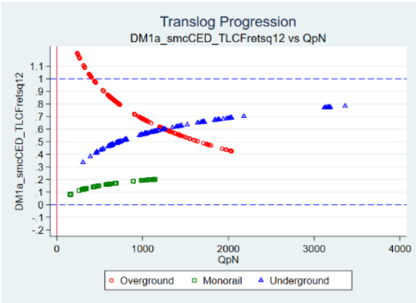
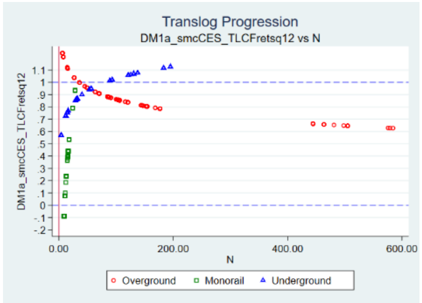
Non-Intuitive findings on CES (convexity and many values below zero for DMU were significant)</td><td>Network
DMO✓
DMM✓
DMU✓
$Network^2$
DMO×
DMM✓
DMU✓</td><td>Not Applicable</td></tr>
</table>

Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 12 FE +Time	 **Non-Intuitive** findings on CED (convexity and starting values above the unitary line for DMO were significant)	Density DMO✓ DMM✗ DMU✗ Density² DMO✓ DMM✗ DMU✗	 **Non-Intuitive** findings on CES (convexity and many values below zero for DMU were significant)	Network DMO✓ DMM✓ DMU✗ Network² DMO✗ DMM✓ DMU✓	Time✓

Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 12 FE +Time +Time2	 **Non-Intuitive** findings on CED (convexity for DMO was significant)	Density DMO✓ DMM× DMU× Density^2 DMO✓ DMM× DMU×	 **Non-Intuitive** findings on CES (convexity and many values below zero for DMU were significant)	Network DMO✓ DMM✓ DMU× Network^2 DMO× DMM✓ DMU✓	Time× Time^2×

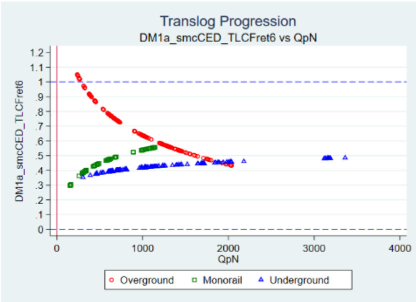
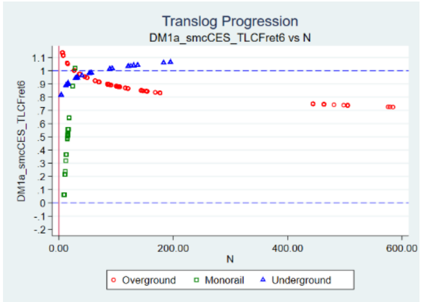
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 12 RE	 **Non-Intuitive** findings on CED (convexity and starting values above the unitary line for DMO were significant)	Density DMO✓ DMM× DMU✓ Density^2 DMO✓ DMM× DMU×	 **Non-Intuitive** findings on CES (convexity and starting values above the unitary line for DMO were significant)	Network DMO✓ DMM× DMU✓ Network^2 DMO✓ DMM× DMU×	Not Applicable

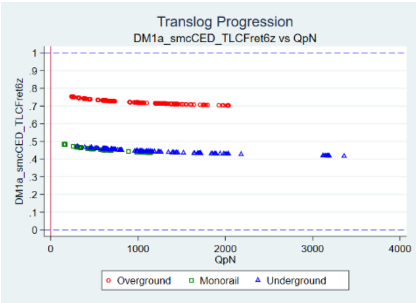
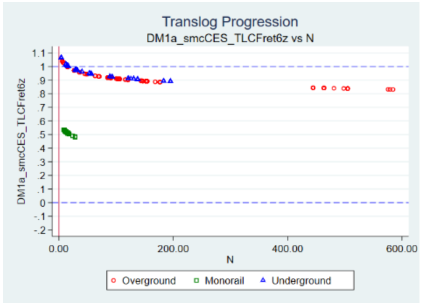
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 12 RE +Time	 **Non-Intuitive** findings on CED (convexity and starting values above the unitary line for DMO were significant)	Density DMO✓ DMM✗ DMU✓ Density^2 DMO✓ DMM✗ DMU✗	 **Non-Intuitive** findings on CES (convexity and starting values above the unitary line for DMO were significant)	Network DMO✓ DMM✗ DMU✓ Network^2 DMO✓ DMM✗ DMU✗	Time✓

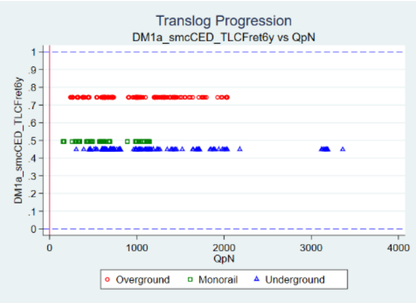
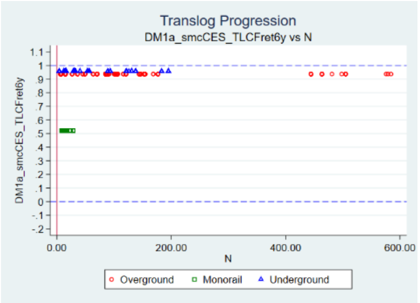
Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 12 RE +Time +Time2	 **Non-Intuitive** findings on CED (convexity and starting values above the unitary line for DMO were significant)	Density DMO✓ DMM✗ DMU✓ Density^2 DMO✓ DMM✗ DMU✗	 **Non-Intuitive** findings on CES (convexity and starting values above the unitary line for DMO were significant)	Network DMO✓ DMM✗ DMU✓ Network^2 DMO✓ DMM✗ DMU✗	Time✓ Time^2✗

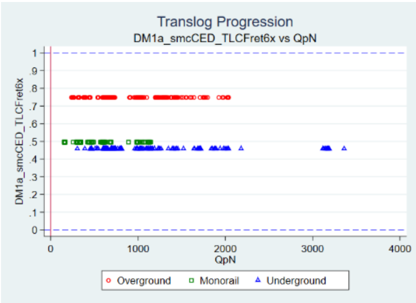
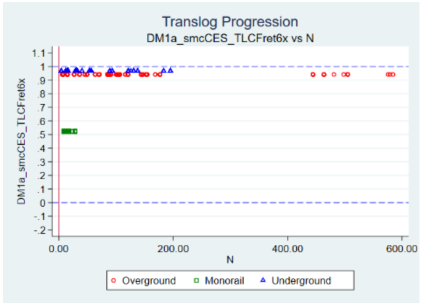
Note: ✓ Significant at 0.05 level ✗ Insignificant at 0.05 level

Table 55. CED and CES generated by several Model 6 RE +Time Reductions

Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6 RE +Time	 **Intuitive** findings on CED (convexity in DMO was insignificant; curvature for DMO, which started with values above unitary, was insignificant)	Density DMO✓ DMM✓ DMU✓ Density² DMO✗ DMM✗ DMU✗	 **Intuitive** findings on CES (curvature for all modes — one of which started with values above unitary — was insignificant)	Network DMO✓ DMM✓ DMU✓ Network² DMO✗ DMM✗ DMU✗	Time✓

Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6z RE +Time (Model 6 plus the removal of mode dummy interactions with Density² and Network²)	 **Intuitive** findings on CED (convexity in DMO, DMM and DMU was insignificant)	Density DMO✓ DMM✓ DMU✓ Density²✗	 **Intuitive** findings on CES (convexity for DMO and DMU was insignificant; curvature for DMO and DMU, which started with values above unitary, was insignificant)	Network DMO✓ DMM✓ DMU✓ Network²✗	Time✓

Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6y RE +Time (Model 6z plus the removal of Density^2 and Network^2)	 **Intuitive** findings on CED	Density DMO✓ DMM✓ DMU✓	 **Intuitive** findings on CES	Network DMO✓ DMM✓ DMU✓	Time✓

Model	CED		CES		Time Variable
	Graph	Significance	Graph	Significance	Significance
Model 6x RE +Time (Model 6y plus the removal of interaction between Density and Prices)	 **Intuitive** findings on CED	Density DMO✓ DMM✓ DMU✓	 **Intuitive** findings on CES	Network DMO✓ DMM✓ DMU✓	Time✓

Note: ✓ Significant at 0.05 level ✗ Insignificant at 0.05 level