The impacts of moving block signalling on technical efficiency: An application of propensity score matching on urban metro rail systems

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ABSTRACT
This study tests the effect that introducing moving block signalling has on the technical efficiency of urban metro rail systems using a panel dataset of 27 urban metro systems across 20 countries for the period 2004 to 2012. By considering moving block signalling as a treatment it is possible to measure the effect that the associated benefits bring to output efficiency levels. The study calls upon stochastic frontier analysis (SFA) to estimate technical efficiencies for each metro, and then applies propensity score matching (PSM) to evaluate the effect of the type of signalling on technical efficiency. The study allows for accounting of confounding factors and the selection of appropriate reference groups. To the best of our knowledge, the study is novel in its provision of empirical evidence of this nature, and the results indicate that the technical efficiency of a metro can be improved by 11.5%.
INTRODUCTION
Amongst the more successful transport solutions in large urban cities has been the high capacity and high frequency services provided by metro rail systems (hereafter referred to as metros). In busy cities, this success has led to significant challenges for metros to be able to deliver sufficient capacity to meet growing demand. However, metros require significant expenditures, both in terms of operating costs and capital investment. In most cities some degree of public funding from governments is required, whether it is for initial or ongoing investment in infrastructure or to subsidise operating costs [1]. Even metros that are able to cover their own costs may still receive compensation payments for reducing fares for socio-economic groups. Because of the large investments made in metros and the need for greater capacity, it is clear that operators must be as efficient as possible, and any avenues that potentially increase efficiency warrant closer investigation.

In order to gauge the performance of a metro, a valuable measure of how effectively a metro is operating is technical efficiency. The concept of technical efficiency is described in more detail below in Section 2, however it can conventionally be described as the effectiveness with which a firm produces output given the set of inputs that it uses. In the context of metros, standard input factors of production include labour, capital and energy. These are used to produce output, which for metros includes intermediate outputs such as car kilometres, and final outputs such as passenger kilometres or passenger journeys. Ultimately, technical efficiency can provide critical insight into efficiency gaps experienced by metros. It is worth noting that to gain an overall impression of economic efficiency it is necessary to consider allocative efficiency in addition to technical efficiency, which involves selecting the mix of inputs that produces output at minimum cost. However, for the purpose of this study focus is solely placed on technical efficiency.

One of the many inhibitors of achieving satisfactory technical efficiency levels includes capacity challenges faced as demand for public transport has increased. These can manifest in the stations and on platforms in the form of queues and increased boarding and alighting times, but can also occur on track between stations if trains impede each other’s progress. The practice of adjusting service patterns to skip less busy stations, referred to as “Skip-Stop”, can be used to aid in alleviating congestion, Lee [2]. However, the development of new signalling technology and the increasing potential to automate operations have created opportunities for metros to increase capacity.

In order to avoid consecutive trains colliding on the same track, conventional signalling systems divide the track into sections known as “blocks”. Traditionally, when a train occupies any part of a block, that block and a “buffer” block behind it are made unavailable for the following train to enter, to avoid collisions. This is referred to as fixed block signalling, as these blocks are at fixed points on the line. A major technical development in recent years has been the introduction of what is known as moving block signalling. Under a moving block system, the “safe zone” between trains is dynamic and determined by the exact position and speed of each train (i.e. slower moving trains can operate closer together given their shorter stopping distances), thus relieving the capacity restrictions imposed by static fixed blocks. This is illustrated in FIGURE 1, where the indicative braking curves for the trains are shown (the y-axis being speed, and the x-axis being braking distance). In the fixed block case, the pursuing train is confined by the fixed point on the track (represented by the black square in the figure). On the other hand, the train on the moving block system enjoys no such restrictions, allowing for a shorter headway between the trains if respective positions, speeds and braking distances allow.
This means that in many circumstances, moving block signalling enables trains to be operated at higher frequencies.

However, changing from traditional to moving block signalling is a technological step change. It requires significant investment in time and money and introduces considerable risks for operators. The key risks are the potential for disruptions to service (during installation, testing, and initial operations), and those risks associated with changing to a less mature and more complex computerised technology. For a metro operator to consider a transition, it is therefore crucial to understand the impacts of moving block signalling.

Consequently, this study aims to provide additional insight by empirically testing the effect of introducing moving block signalling on the technical efficiency of a metro. To the best of our knowledge, this is the first study to provide empirical evidence of this nature. The study hypothesises that metros that use moving block signalling are able to carry out their production process more efficiently and anticipate that the results will be able to aid judgement for metros reviewing their signalling technology.

The paper is structured as follows. Section 2 introduces the concept of productivity, followed by a brief explanation of technical efficiency and the two avenues that have been examined for its measurement. Section 3 describes moving block signalling and the necessary systems required for its operation, followed by briefly exploring potential impacts based on current literature. Sections 4 and 5 describe the methodology and data, while section 6 presents and discusses the main results, and finally section 7 draws together the main conclusions.

PRODUCTIVITY AND TECHNICAL EFFICIENCY
In general, productivity can be described as the ratio of a firm’s outputs to its inputs. In its simplest form, such as a single output being produced for a single input that is used, calculations are uncomplicated. However for a multi-input/analysis, such as metros, calculations are far from straightforward. Technical efficiency, on the other hand, refers to how close a firm operates to its maximum attainable output. In order to understand the difference it is important to be acquainted with the notion of a production frontier, which represents the output attainable from each input level. Accordingly, given a set of inputs, a metro is considered fully technically efficient if its output lies on the production frontier, while beyond the frontier is simply not feasible, and below represents inefficiency indicating that not all resources are being used at an optimal level. FIGURE 2 below helps illustrate these concepts. The distinction between productivity and technical efficiency is important when considering scale economies. For example, if a metro is operating at an optimally technically efficient level, it is still possible to increase productivity by increasing the scale of the system. Evidently, the concept of scale is an important factor to consider when making comparisons between metros. Coelli et al. [3] provide a comprehensive review of production economics giving an overview of methods and measurement concepts.

Contemporary approaches towards productivity measurement can generally be categorised into non-parametric and parametric studies. Non-parametric approaches to productivity measurement have been widely used throughout multiple industries, mainly as they can be directly constructed from data without the need for statistical estimation of a production function. The most favourable deterministic non-parametric approach is that of Data Envelopment Analysis (DEA), of which Charnes et al. [4] set the foundations. To the best of our knowledge, the sole examples of empirical studies conducted to estimate efficiency specifically for urban rail systems have been carried out using DEA. These include Santos et al. [5] who
estimate technical efficiency for 37 European metros, Tsai et al [6] who used DEA to measure the cost efficiency of 20 International metros, and Graham [7], this time on 99 urban rail systems across the world.

The most prominent parametric approach is that of Stochastic Frontier Analysis (SFA). SFA involves specifying a functional form and has the benefit of allowing for dealing with error in the data and for statistical hypothesis testing. The stochastic frontier production function model was simultaneously proposed by Aigner et al. [8] and Meeusen and Broeck [9]. Comprehensive overviews of the econometric developments of SFA are summarised in Kumbhakar and Lovell [10] and Coelli et al. [3], while Gong and Sickles [11] provide a fairly comprehensive review of the comparative performance between DEA and SFA using a Monte Carlo technique. Despite SFA assumptions about functional form and distributions, it remains the preferred option for calculating the technical efficiency scores for this study to avoid bias by outliers and allow for measurement error in the data and other statistical noise.

**MOVING BLOCK SIGNALLING**

Traditional fixed block systems detect a train’s location using fixed track circuits, and control permission to proceed via line-side signals at the beginning of each block. In order for moving block signalling to be implemented, a number of complementary systems need to be in place. To enable moving blocks, a system is required that can pinpoint the location of a train to a greater level of precision, and control the train’s permission to proceed forward in a dynamic way that is constantly updated. Communications Based Train Control (CBTC), a system which enables control of a train via communication between trains and wayside equipment (usually through radio transmission), provides this capability. Consequently, the exact location and speed of the trains is always known, and permission to proceed and the allowable speed are communicated from the system to the train.

Other relevant systems include Automatic Train Protection (ATP), which maintains fail-safe protection against collisions, Automatic Train Control (ATC), which is the system for automatically controlling train movements (e.g. re-routing or holding trains to even out the service), and Automatic Train Operation (ATO), which is a subsystem of ATC that automatically carries out driving actions such as accelerating and braking (typically performed by train operators on a fully manual line). These three systems can all be implemented in either a fixed- or moving-block environment, but are optional for fixed block whereas they are necessary for moving block. Under a railway context (e.g. suburban/intercity/freight), particularly in the United States, the term Positive Train Control (PTC) is used to refer to a system which imposes speed and signalling restrictions in order to provide protections associated with ATP. TABLE 1 summarises the allowable combinations of system technologies for metro railways. Some of the technical intricacies are covered in more detail in Newman [12], Gill [13, 14], Ferrari et al. [15, 16], and the British Standards Institution (BSI) standard [17].

Previous research assessing moving block signalling has predominantly been rooted in simulation studies, with focus targeted at service optimisation and maximising energy efficiency. Early examples from railway include Hill and Bond [18] and Ho et al. [19]. The first notable example of research conducted for metros affirming the capacity benefits of moving block signalling stems from Gill [14], who also highlights moving block signalling offering improved safety, reduced costs from less necessary wayside equipment, and finally operational flexibility allowing for faster recovery from disruptions. A more recent study on metros includes Takeuchi
et al. [20], who confirms through both mathematical analysis and simulation studies that moving block signalling can achieve improved capacity. However, it appears that no studies have provided an indication of the magnitude of impact moving block signalling has on a metro as a whole, nor has there been a study carried out using observational data.

Elsewhere, there is also evidence provided by Melo et al. [21], which indicates that ATO can notably reduce the occurrence of incidents in metros. Results indicate that moving from manual train operation to ATO is associated with a 33% reduction in incidents. While the study tested specifically for ATO versus manual operation (GoA2, 3 & 4 versus GoA0/1), it can be inferred from Melo et al.’s results that CBTC may offer improved reliability as many ATO systems rely on CBTC while CBTC is rarely used for manual operation. Furthermore, by using radio-based communication, much of the wayside equipment necessary for fixed block signalling becomes redundant [14]. This in turn may curtail costs and disruption caused by maintenance.

Conversely, it is also important to acknowledge potential hindrances that modern signalling systems may encounter, some of which may limit the additional capacity to be gained. Studies such as Chow [22] and Lin et al. [23] remind us that there are vital considerations to be made to ensure ventilation and smoke control systems are adequate, particularly for metros which operate in deep tunnels. This has the potential to inhibit allowable train frequency in order to allow for air circulation at critical times, and reduce the heating effect of trains which is generated on a per train basis [24].

METHODOLOGY
Stochastic Frontier Analysis (SFA)
As discussed above Stochastic Frontier Analysis (SFA) is carried out to estimate the technical efficiency scores for each metro. A stochastic frontier production function model under a panel data specification can be presented as follows:

\[ y_{it} = f(x_{it}; \beta) + \varepsilon_{it} \]

\[ \varepsilon_{it} = v_{it} - u_{it} \]

Here the dependent variable is output, \( y_{it} \), of the \( i \)-th firm in the \( t \)-th time period, while the explanatory variables are input quantities, \( x_{it} \), of the \( i \)-th firm in the \( t \)-th time period, and \( \beta \) is a vector of unknown parameters associated with the inputs. The key aspect of SFA is the introduction of two separate disturbance terms, which capture the true random differences, \( v_{it} \), and the efficiency differences, \( u_{it} \), separately. The efficiency gap of a metro can be obtained from the relationship between the actual output level \( y \), and the maximum attainable potential output \( y^* \) determined by the estimated production frontier. A metro found to be operating on the frontier is said to be fully technically efficient, while a metro functioning below the frontier is considered technically inefficient, as illustrated in FIGURE 2 above. Efficiency scores are obtained from the ratio of \( y/y^* \), and hence can measure the degree of output efficiency of a given metro.

A translog (transcendental logarithmic) production function is selected, which is a generalised cobb-douglas function consisting of both linear and quadratic terms and has the ability to contain multiple factor inputs also allowing for interactive terms. It is considered a
flexible functional form as it provides a second order Taylor approximation to an unknown technology, imposing minimal structure to the production frontier. It imposes fairly unrestrictive assumptions on the elasticities of production, the elasticities of substitution between the inputs, and returns to scale. A four input (labour, track, fleet, stations) translog production function written in terms of logarithms can be presented as in equation (3). An explanation for the choice of input factors is provided in the data section below.

\[
\ln Y = \alpha + \beta_L \ln L + \beta_T \ln T + \beta_F \ln F + \beta_S \ln S \\
+ \frac{1}{2} \beta_{LL} (\ln L)^2 + \beta_{LT} \ln L \ln T + \beta_{LF} \ln L \ln F + \beta_{LS} \ln L \ln S \\
+ \frac{1}{2} \beta_{TT} (\ln T)^2 + \beta_{TF} \ln T \ln F + \beta_{TS} \ln T \ln S \\
+ \frac{1}{2} \beta_{FF} (\ln F)^2 + \beta_{FS} \ln F \ln S \\
+ \frac{1}{2} \beta_{SS} (\ln S)^2 \\
+ \theta \text{year} - u + v
\]

Where \( \alpha \) is the constant, the \( \beta \)'s are the parameters and interactive parameters to be estimated and are associated with labour, track, fleet and stations. As discussed, the error term is decomposed into the estimate of technical efficiency \( u \), and a stochastic error term \( v \). A time trend \( \text{year} \) is included to account for technological change, with \( \theta \) being the unknown parameter to be calculated.

It follows that the technical efficiency of production is defined by equation (4).

\[
TE_{it} = \exp(-u_t)
\]

The method of maximum likelihood is used to simultaneously estimate the parameters of the stochastic frontier and the model for the technical inefficiency effects. This technique chooses estimates that make the actual observations as likely as possible so that they maximise the likelihood function, which is expressed in terms of the following variance parameters:

\[
\sigma^2 = \sigma_v^2 + \sigma_u^2
\]

\[
\gamma = \sigma_u^2 / (\sigma_v^2 + \sigma_u^2)
\]

By differentiating equation (3) with respect to each factor input, the marginal elasticities of output with regard to each input are obtained, as shown by equations (7-10). Summing these provides us with estimates for Returns to Scale (RTS), equation (11).
\[
\begin{align*}
\delta \ln Y / \delta \ln S &= \beta_S + \beta_{SL} \ln L + \beta_{ST} \ln T + \beta_{SF} \ln F + \beta_{SS} \ln S \\
RTS &= \delta \ln Y / \delta \ln L + \delta \ln Y / \delta \ln T + \delta \ln Y / \delta \ln F + \delta \ln Y / \delta \ln S
\end{align*}
\]

(10)\hspace{1cm}(11)

Economies of scale measure how the output responds as inputs are increased proportionally. Constant returns to scale imply that if inputs are increased, outputs will increase with the same proportion. The delta method is called upon to provide information on the statistical properties of the elasticities, Oehlert [25].

**Propensity Score Matching (PSM)**

Advances in the methodological techniques for estimating causal inference largely stem from the field of medicine. This is a direct response to studies being unable to carry out randomised clinical trials, either because it is often unfeasible or unethical. As such, the relatively novel approach of propensity score analysis has been developed for evaluating treatment effects using non-experimental or observational data. Guo and Fraser [26] provide the full history of development of propensity score analysis from the seminal work of Rosenbaum and Rubin [27]. Further comprehensive overviews and explanations are provided by, amongst others, Peikes et al. [28], and Caliendo and Kopeinig [29].

This study proposes that by considering moving block signalling as a treatment, it is possible to embrace a propensity score analysis approach to estimate the impact of this type of signalling on technical efficiency scores, and consequently provide a good indication of differences in performance experienced by metros. In summary, the procedure involves finding a set of metros that are comparable for treatment analysis based on their probability of receiving treatment conditional on observed baseline characteristics. This simplifies the matching process greatly and eliminates bias created by confounding factors (covariates that affect both the probability of treatment exposure and potential outcomes).

To carry out the procedure, firstly the probability of receiving treatment is estimated by calculating the propensity scores. This study uses the following probit model:

\[
P(T = 1 \mid C) = \frac{\exp(\alpha + \beta'C)}{1 + \exp(\alpha + \beta'C)}
\]

(12)

where \( \alpha \) is the intercept and \( \beta' \) is the vector of regression coefficients associated with the confounding factors, \( C \). Once the propensity scores are matched and compared, it is possible to identify the causal effect and the average treatment effect for the treated (ATT) is calculated by:

\[
\delta_{ATT} = E(Y \mid T = 1, p(T = 1 \mid C)) - E(Y \mid T = 0, p(T = 1 \mid C))
\]

(13)

Where \( T \) denotes the treatment status, while \( Y \) denotes the technical efficiency. The key advantage of this technique is the ability to build the model in such a way that the effects of confounding are eliminated. Furthermore, by grouping metros based on a propensity score, similar metros are clearly defined and selection bias is avoided ensuring that the difference
between treatment and control metro groups can be attributed to moving block signalling. For a comprehensive overview of the technique and assumptions refer to Guo and Fraser [26].

DATA
The main source of data originates from two consortia of metro system operators, namely the Community of Metros (CoMET) and the Nova Group (Nova), managed by the Railway and Transport Strategy Centre (RTSC) based at Imperial College London. The consortia focus on benchmarking, and the work developed by the RTSC over the last two decades is supported by a comprehensive database of key performance indicators related to different areas of metro operation. For the purpose of this specific study, data is used for output and input factors to estimate technical efficiency (the response variable), the type of signalling (the treatment variable), as well as a set of confounding variables. Accordingly, the data allows us to compile an unbalanced panel data set consisting of 27 metro systems over 9 years between 2004 and 2012. CoMET metros incorporated in the study include Beijing, Berlin, Hong Kong, London, Mexico City, Madrid, Moscow, New York, Paris (two systems), Santiago, Shanghai, Sao Paulo and Taipei, while NOVA metros include Buenos Aires, Barcelona, Bangkok, Delhi, Lisbon, Milan, Montreal, Newcastle, Naples, Rio de Janeiro, Singapore, Sydney and Toronto.

This study is encouraged by a high-standard level of data quality, as during the years of benchmarking work carried out within the groups, a series of systematic data cleaning processes have been developed and maintained which carry out verification and validation tests. This is complimented by ongoing contact with CoMET and Nova members through phone calls, face-to-face meetings, and site visits. TABLE 2 presents an overview and descriptive statistics of the variables that have been compiled for this study. It is also worth noting here that due to the sensitive commercial nature of the RTSC data, an existing confidentiality agreement requires results to be presented in an anonymised form.

For estimating the technical efficiency, our response variable, standard microeconomic theory advises factors of production for a firm to typically include capital, labour, energy, material inputs and purchased services. This classification of inputs is commonly referred to as the KLEMS approach [3]. For the case of metros three capital factors are considered, namely track (total length of network used by trains operating in passenger service, also referred to as network length), fleet (total number of cars), and the number of stations served. For labour, total own staff and contractor hours worked are incorporated. Total energy consumption was excluded as an input factor as traction energy is directly related to the size of the fleet and network length, while non-traction energy is directly related to the number of stations. Therefore, the levels of energy are adequately captured by the selected inputs. Material inputs and purchased services were also excluded as they are not applicable for this particular study. For output, the study considers data for actual revenue operated car kilometres. This includes all car kilometres which were actually operated in revenue service, and excludes empty stock movements, movements from depots, engineering trains, driver training runs, cancellations of scheduled runs, and rail replacement bus services. Under a production function specification, the model is limited to a single output factor. Consequently a train, as opposed to a passenger orientated output, is selected as metros tend to have a greater degree of control over these types of output. Furthermore, due to the more stochastic nature of passenger orientated measures of output it is evident that these cannot be represented as accurately.
Moving now to the treatment effect variable. As alluded to above where moving block signalling is introduced and discussed, this treatment is somewhat of a composite measure. The variable does not disassociate itself from the necessary communication and automation systems required to enable moving block signalling. The variable is binary, and assigned 1 if the system utilises moving block signalling, and 0 otherwise.

Focusing now on the confounding variables, which are the set of variables believed to have an effect on both the technical efficiency and the type of signalling. Firstly, the study considers a network density variable, which is the ratio of the network length and the number of stations. As metros exhibit returns to density [30], dense networks are more likely to exhibit higher technical efficiency levels. In a dense network with shorter distances between stations, there is also a greater likelihood of trains being impeded by the train traffic in front of them, due to less distance between stops. Therefore these networks may be more likely to adopt moving block signalling as it enables trains to operate closer together. Secondly, the study considers a reliability measure to account for potential reductions in incidents causing delay, ultimately leading to improved efficiency levels. This is partly because moving block systems are a newer technology, and so are most often installed either on newer metros (which tend to have higher reliability), or as a replacement for a life-expired traditional signalling system, where the reason for replacement would usually be an end of life decline in reliability. It is also because moving block systems are frequently used in conjunction with ATO, which in turn is associated with higher reliability. For this measure the average car kilometres travelled between failures is used, where a failure constitutes a disruption to the service of 5 minutes or longer. Adopting CBTC and moving block signalling can also reduce the amount of wayside equipment required; this in turn may reduce maintenance costs. As such, a measure of the maintenance costs is considered. Finally, the proportion of track which operates in deep tunnel to acknowledge potential ventilation and smoke control system restrictions is also considered.

RESULTS
Descriptive statistics of the technical efficiency scores estimated from the SFA model and the propensity scores estimated from the probit model are presented in TABLE 3. The technical efficiency scores provide us with an indication of relative technical performance between the metros. As discussed, these form the response variable used in the PSM procedure. Regarding the elasticities the study finds elasticity of output with respect to labour, track, fleet, and stations to be 0.11, 0.28, 0.89 and -0.28 respectively. Regarding RTS, the study finds constant returns to scale as the output of elasticities with respect to each of the input variables sum to 1 as described in equation (11). This suggests that a proportional increase in input levels will increase output levels with the same proportional increase. As alluded to, the propensity scores calculated by the probit regression are used to estimate the probability of a metro being selected in the treatment group.

Before considering these results and using them to estimate the effects of moving block signalling on technical efficiency, it is first necessary to carry out a couple of diagnostic tests to check the validity of using a PSM approach. Firstly, a visual inspection of the propensity score distribution for the treated and untreated groups is carried out. FIGURE 3 illustrates the relevant distributions and favourably indicates that there is sufficient overlapping of the distributions.

Secondly, a balancing test is performed to assess the matching quality. TABLE 4 presents the t-test of covariate means between the treated and control groups. The test verifies
that there are no significant differences between the covariate means of the treated and control groups, and verifies that the treatment is independent of the covariates after matching. As such, the diagnostic tests appear to show that the PSM method is indeed suitable and the results obtained are considered robust.

Finally, moving to the primary focus of this study, **TABLE 5** presents the average treatment effect for the treated (ATT). The t-statistic takes a value of 1.72, which indicates a confidence level of 91.5%. From this the study concludes that the estimate for the treatment effect has an acceptable level of significance given sample size, hence the study can infer that moving block signalling has a causal effect on technical efficiency. From the magnitudes the study finds that the difference between the respective technical efficiencies of the treated and untreated metros is a substantial 11.5%. Ultimately, the results suggest that implementing moving block signalling can dramatically improve the ability of a metro to produce car kilometres more efficiently, given its labour and capital inputs. In turn, the results obtained provide insight that is beneficial to metro systems that are experiencing capacity restrictions, and could consider transferring to a moving block signalling system.

**CONCLUSION**

This paper conducted empirical work using SFA to estimate the performance of metro systems by calculating technical efficiency scores. The study proposes that by considering moving block signalling as a treatment, it is possible to gain an improved understanding of the impacts that this type of signalling imposes on the efficiency levels of metro systems by using the causal inference technique of PSM. In doing so the approach accounts for confounding factors and the selection of appropriate reference groups. This contribution is considered useful in light of metros facing increased capacity challenges. To the best of our knowledge, the study is novel in its provision of empirical evidence which provides quantification from observed data, rather than expected impacts from simulation.

The results indicate that the technical efficiency of a metro can be improved by 11.5% from improvements offered by moving block signalling and associated automation experienced on urban metro rail systems. This suggests that it is more probable that a metro is able to provide an adequate service under moving block, and perhaps also suggests that it may be possible to implement more aggressive scheduling.

As for future work, data permitting, it may also be possible to analyse the proportion of metro system that use moving block signalling and carry out a study based on line level data as opposed to the whole system. By considering the system as a whole it is possible that the results may be understated. There is also scope to try and disentangle the composite nature of the moving block signalling variable, and consider the complimentary systems of CBTC, ATP, ATO, and ATC independently. There may also be potential to investigate the effectiveness of skip-stop operation in the future in a similar manner using PSM as metro systems adopt the strategy.
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FIGURE 1  Fixed and Moving block signalling
FIGURE 2  Production frontier
### TABLE 1  Combinations of signalling technologies

<table>
<thead>
<tr>
<th>Grade of Automation</th>
<th>Fixed Block</th>
<th>Moving Block</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manual</td>
<td></td>
<td></td>
</tr>
<tr>
<td>without ATP</td>
<td>GoA0</td>
<td>✓</td>
</tr>
<tr>
<td>with ATP</td>
<td>GoA1</td>
<td>×</td>
</tr>
<tr>
<td>Automatic: ATP, ATC &amp; ATO</td>
<td>GoA2, 3 or 4</td>
<td>✓</td>
</tr>
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<td></td>
<td></td>
<td>✓</td>
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- can be CBTC
- always CBTC
TABLE 2  Variables and Descriptive Statistics for 27 Metro Rail Systems 2004-2012

<table>
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<tr>
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<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
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<td>Output</td>
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<td></td>
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<tr>
<td>Actual revenue operated car km (millions)</td>
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<td>162.41</td>
<td>176.28</td>
<td>4.23</td>
<td>737.00</td>
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<tr>
<td>Input</td>
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<tr>
<td>Labour (total own and contractor hrs, millions)</td>
<td>197</td>
<td>17.18</td>
<td>16.00</td>
<td>0.56</td>
<td>64.56</td>
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<tr>
<td>Track (operational km)</td>
<td>211</td>
<td>175.16</td>
<td>214.19</td>
<td>13.30</td>
<td>1,128.00</td>
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<tr>
<td>Fleet (total number of cars)</td>
<td>208</td>
<td>1,500.17</td>
<td>1,578.70</td>
<td>51.00</td>
<td>6,417.00</td>
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<td>Stations (number)</td>
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<td>122.68</td>
<td>102.74</td>
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<td>424.00</td>
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<td>Treatment</td>
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<td>208</td>
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<td>0.44</td>
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<td>1</td>
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<td>Network density (network length/no.stations)</td>
<td>197</td>
<td>1.27</td>
<td>0.56</td>
<td>0.60</td>
<td>3.67</td>
</tr>
<tr>
<td>Reliability (car km between failures)</td>
<td>187</td>
<td>0.36</td>
<td>0.68</td>
<td>0.00</td>
<td>3.21</td>
</tr>
<tr>
<td>Maintenance cost (maintenance cost per car km)</td>
<td>167</td>
<td>0.36</td>
<td>0.09</td>
<td>0.20</td>
<td>0.73</td>
</tr>
<tr>
<td>PSM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Deep tunnel (% track deep tunnel)</td>
<td>174</td>
<td>0.50</td>
<td>0.32</td>
<td>0.01</td>
<td>1.00</td>
</tr>
</tbody>
</table>
TABLE 3  Descriptive statistics of technical efficiency scores from SFA and propensity scores from probit regression

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technical efficiency scores</td>
<td>0.841</td>
<td>0.119</td>
<td>0.553</td>
<td>0.993</td>
</tr>
<tr>
<td>Propensity scores</td>
<td>0.113</td>
<td>0.066</td>
<td>0.000</td>
<td>0.327</td>
</tr>
</tbody>
</table>
FIGURE 3  Propensity score distribution
| Variable        | Mean | % bias | t  | p>|t| |
|-----------------|------|--------|----|-----|
| Treated         | Control |        |    |     |
| Network density | 1.18 | 0.95   | 42.4 | 1.68 | 0.11 |
| Reliability     | 0.15 | 0.08   | 9.2  | 1.20 | 0.24 |
| Maintenance Cost| 2.94 | 2.20   | 1.6  | 1.16 | 0.26 |
| Deep tunnel     | 0.42 | 0.47   | -19.8 | -0.45 | 0.66 |
**TABLE 5**  Effects of moving block signalling on technical efficiency

<table>
<thead>
<tr>
<th>Sample</th>
<th>Treated</th>
<th>Controls</th>
<th>Difference</th>
<th>S.E.</th>
<th>T-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unmatched</td>
<td>0.906</td>
<td>0.875</td>
<td>0.031</td>
<td>0.039</td>
<td>0.79</td>
</tr>
<tr>
<td>ATT</td>
<td>0.906</td>
<td>0.791</td>
<td>0.115</td>
<td>0.067</td>
<td>1.72</td>
</tr>
</tbody>
</table>