Benchmarking Road Traffic Safety Across OECD Countries

A Distance Function Approach

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Abstract
This study combines an economic production framework with a latent risk theory framework to examine improvements in road safety performance of thirteen Organisation for Economic Co-operation and Development (OECD) countries for the period 1975–2004. We find that, on average, total factor productivity in road safety increased by 2 per cent per annum over the past 30 years. We also find that technological progress has been the main contributor to improvements in road safety. Indicators of economic activity, including the employment rate and CO₂ emissions per capita as well as population density, are positively associated with improvements in traffic safety.

Date of final version: March 2015
1.0 Introduction

Road traffic collisions (RTCs) rank as the tenth-highest cause of death and disability in the world; they are the greatest killer of people aged ten to 24. The global burden of disease due to RTCs is also forecast to increase over the next two decades, even though some high-income countries (for example, Australia) have been successful in reducing fatalities considerably (for example, by almost 44 per cent) in the period 1990 to 2010 (Kassebaum et al., 2014). Improvements in road traffic safety are thus likely to be sources of substantial public health benefit, and are of interest to a range of interested parties including the general public, government agencies, industry, and researchers. To gain an insight into how road safety has improved across countries, it is therefore of interest to compare how the various middle- and high-income countries have performed in road traffic safety over time. The common indicators that are used to benchmark the road safety performance of countries tend to use partial measures of improvements in safety, or indicators in the latent safety of road use, such as RTC fatality rates and numbers of accidents.

Although such single-measure indicators are useful, the well-being and survival of road users obviously is determined by a multitude of factors that include not only the safety of roads and vehicles, but also factors such as the quality of health systems and health care services, for instance. Few studies — including Odeck (2000; 2005; 2006), Hermans et al. (2008; 2009), Lin et al. (2010), and Shen et al. (2011; 2012; 2013) — have sought to compare the road safety performance of various countries on multiple road safety measures. With the exception of Lin et al. (2010), most of the foregoing studies apply the data envelopment analysis (DEA) method to examine changes in total factor productivity (TFP) in traffic safety using the Malmquist productivity index approach. An obvious advantage of DEA is that it requires no assumption about the production function’s functional form. An important disadvantage, though, is that the distribution of the (in)efficiency components in DEA is highly prone to measurement errors. This is particularly important in the current context, because some of the commonly used exposure measures, such as vehicle kilometres travelled and passenger-kilometres, are known to be subject to serious measurement errors. In this paper, we mitigate the effects of errors in variables by invoking a stochastic frontier analysis (SFA) using the distance function approach. Furthermore, owing to the availability of panel data, we are able to examine TFP growth and its two main constituents: productivity ‘catching-up’ and technological progress (Bartelsman and Doms, 2000). Thus, the present study adds to the literature in three ways: (i) it employs multiple, rather than single indicators of progress in road safety to measure the improvements the study countries have made over a period of three decades; (ii) it does so by implementing an SFA to address an important errors-in-variables problem that may bias the estimates produced to date via DEA; and (iii) it includes a substantial number of possible determinants of efficiency, to analyse their likely influences on the different levels of efficiency that have been achieved by different countries in the sample.

The remainder of this paper is organised as follows. Section 2 reviews the literature on the efficiency of traffic safety initiatives. Section 3 reviews the methodology, and Section 4 discusses the data and selection of variables. Section 5 presents results and Section 6 concludes.
2.0 Literature Review

Since the traffic safety literature is vast (see, for example, Elvik, 2014; Mooren et al., 2014; and Hughes et al., 2015, for comprehensive reviews), we focus on reviewing studies on the efficiency of traffic safety measures. Surprisingly, we were able to find only a handful of studies that fit this narrower definition. In addition, even though the efficiency literature on traffic safety contains some few SFA studies, to the best of our knowledge only one of these analysed data on accidents and the outcomes of accidents. Specifically, Lin et al. (2010) examined the efficiency of ten bus companies in Taipei. These authors used vehicle kilometres as a measure of the output of bus services, and used measures of labour, capital, and fuel as inputs. They constructed an index of traffic safety using number of accidents, minor injuries, major injuries, and fatalities, and this index was treated as an environmental variable that affects efficiency. The authors found that, after controlling for safety index, the efficiency of bus companies improved from 88 to 93 per cent between 2001 and 2006. Unfortunately, they were not able to estimate whether the improvement was due to technological progress, managerial knowhow, or economy of scale.

In our view, this conception of the index of traffic safety as an environmental variable in Lin et al. (2010) is dubious, because elements of the index can in fact be controlled by managers of bus companies, whereas environmental factors are typically conceived as being those variables over which managers have little or no control. Lin et al.’s (2010) choice of the Cobb–Douglas formulation of the production function in that study is also surprising, as that functional form is less flexible than the translog, for instance (for example, the input elasticities in the Cobb–Douglas formulation are constrained to be constant, whereas the translog specification permits an ‘impressive degree’ of nonlinearity (Berndt, 1991)).

For comparison, we also review some noteworthy studies that have applied DEA to multiple or composite measures of output, to study the efficiency of road safety measures. Hermans et al. (2008) carried out one of the earliest studies to use a composite indicator of road safety to benchmark the achievements of European countries in 2003. The authors used a variety of techniques, including factor analysis, analytic hierarchy analysis, budget allocation analysis, DEA, and equal weighting (of indicators), where each of the seven components (alcohol, speed, protective system, visibility, vehicle, infrastructure, and trauma care) has the equal weight of one-seventh when calculating the index of road safety. Briefly, factor analysis aims to reduce the dimension of multiple traffic safety measures; budget allocation uses expert opinions to prioritise contributions of various factors to traffic safety; budget allocation analysis also uses experts’ opinions to rank the relative importance of factors; DEA uses weighted outputs and inputs to calculate productivity; and equal weighting applies the same weight for each of the factors and the total weight of all factors equals to one. The authors found that reducing alcohol use and speed made the greatest contributions to improvements in road safety in their sample (Hermans et al., 2008, Table 3). Using the seven indicators, the authors revealed that Sweden, the United Kingdom, and the Netherlands had the best road safety performance in 2005.

In a subsequent paper, Hermans et al. (2009) applied DEA to measure road safety in twenty-one European countries in 2003 using eight indicators of safety: the traffic fatality rate; the traffic injury rate; the rate at which tested traffic users were under the mandated blood alcohol content (BAC) limits; the rate of traffic users travelling under speed limit; the rate of seat belt use; the proportion of cars less than six years old; motorway density;
and the rate of health expenditure in GDP. The authors found that countries with the best performance on road traffic safety were Denmark and the Netherlands. They also provided recommendations for inefficient countries to improve road safety based on six indicators (alcohol and drugs, speed, protective systems, vehicle, infrastructure, and trauma care). Their findings led them to suggest different areas of policy emphasis for different countries: for example, they argued that Austria should place greater emphasis on protective transport systems, while the United Kingdom should focus on improving trauma care. The authors did not, however, subject these results to a sensitivity analysis in order to mitigate against a weakness of DEA; namely, its susceptibility to bias due to an errors-in-variables problem.

Shen et al. (2011) investigated the efficiency in traffic safety of nineteen European countries in 2007. The authors applied a multiple-layer DEA approach to produce weight restrictions according to a hierarchy of safety performance indicators. The use of a multiple-layer DEA is an interesting approach, although a weakness of that approach is that no clear rationale has been established for the sequence in which indicators ought to be placed in the ‘multiple layers’. Additionally, the effects of indicator characteristics such as road type (urban roads, rural roads, and motorways), safety systems (seat belts, child restraints, and helmets), and speed (the mean speed and the fraction of the mean to the speed limit) can be used in second-stage regressions. This approach is also data intensive, demanding a wide range of data to be collected, which is often infeasible.

Shen et al. (2012) applied DEA for target setting and benchmarking of road safety in twenty-seven European countries in 2008. They modified the standard DEA model to road safety by rendering the problem one of input minimisation rather than its alternative, maximisation problem. Arguably a simpler alternative to their approach is simply to transform inputs and outputs (for example, by taking the inverse), and apply the standard DEA technique. The authors selected three inputs (population, passenger-kilometres, and passenger cars) and one output (fatalities). They found that the United Kingdom and Malta are fully efficient in traffic safety, followed closely by Sweden and the Netherlands. As with Shen et al. (2011), Shen et al. (2012) neither conducted sensitivity analysis nor examined the factors that might affect the efficiency, leaving their results vulnerable to the errors-in-variables problem.

Shen et al. (2013) measured productivity growth in traffic safety of twenty-six European countries from 2001 to 2010 using the Malmquist productivity index. The authors also selected population, passengers-kilometres, and passenger cars as inputs, and road fatalities as outputs. In a cross-sectional DEA, the authors found that the United Kingdom, Sweden, and the Netherlands were the most efficient producers of traffic safety during the study period. They also found that the main factor contributing to the growth in traffic safety of the study countries was technological progress. Technical efficiency, they found, remained almost unchanged. This study also did not involve any attempts to mitigate the effects of the measurement error that are likely to be present in data such as these, although the short study period may play a mitigating role.

Overall, we could locate only one SFA study that analysed data on accidents and their consequences (that is, Lin et al., 2010), and this study leaves ample room for improvement: for example, by conceiving of safety as a managerial responsibility rather than an environmental variable, invoking a flexible functional form, and measuring productivity growth and its components. The extant literature applies DEA, but does not conduct any analyses that would address the potential for biased results due to an errors-in-variables problem.
3.0 Methodology

3.1 Conceptual framework
We apply two theories to measure and benchmark road traffic safety: production function theory and latent risk theory. The former argues for the existence of a production frontier along which firms — or, in our case, countries — can optimise their input–output combinations. The latter suggests that risk outcomes can be decomposed into three components: exposure, frequency, and severity. From the production viewpoint, countries are only able to move towards the frontier by minimising the inputs they use or, alternatively, by maximising outputs from the inputs available (Deaton and Muellbauer, 1988). In the RTC literature, though, safety outcomes are often measured by the decline in ‘bads’, such as RTC fatalities, rather than goods. Thus, we formulate our dependent variables as the inverse of RTC fatalities and the inverse of RTC injuries. These may be interpreted, in turn, as the inverse odds of deaths and injuries from road traffic accidents. The inputs in the production process of traffic safety then include indicators of investment in traffic infrastructure (for example, roads and road furniture), police enforcement (for example, the use of speed cameras and red-light cameras), and investment in education programmes and in trauma care.

Based on the latent risk theory (Bijleveld et al., 2008; Dupont et al., 2014), we argue that risk outcomes such as traffic fatalities are the product of exposure and frequency of risk. In line with the existing literature, we choose vehicle kilometres travelled (VKT) as the main variable to represent exposure. This variable, however, fluctuates considerably over time, and hence we expect it may be the subject to an error-in-variables problem. Thus, we also use the number of vehicles per 1,000 inhabitants to represent exposure for the purposes of conducting sensitivity analyses.

Overall, by combining the production function and risk theories, we seek to measure the efficiency in traffic safety of countries by comparing the inputs (investment in traffic infrastructure, trauma care, traffic exposure) and outputs (the inverse odds of traffic injuries and fatalities). This assists us to select variables, and to make the necessary data transformations that enable us to apply the standard efficiency measurement techniques such as DEA and SFA without the need to modify the methods themselves.

3.2 The distance function and its estimation
The concept of distance function was proposed by Malmquist (1953) and Shephard (1953), but Farrell (1957) pioneered its application to efficiency measurement. In general, the distance function measures the distance between the observed input–output combination to the ideal input–output combinations on the efficiency frontier. Defining \( x \in \mathbb{R}^k_x \) as the vector of inputs, \( y \in \mathbb{R}^k_y \) as the vector of outputs, for a given technology \( T \), the production process of a firm at period \( t \) may be defined as:

\[
T^t = \{(x', y') : x' \text{ can produce } y'\}.
\]
A distance function can be measured either by focusing on inputs (the minimisation of inputs while producing a given level of outputs) or outputs (maximising output from a given combination of inputs). Thus, an output distance function (\(D_O\)) at period \(t\) of a firm is defined as a technology for which, given input quantity, the output level can be expanded by \(1/\theta\) (0 < \(\theta\) < 1):

\[
D'_O(x', y') = \text{Min}_\theta \left\{ \left( x', \frac{y'}{\theta} \in T \right) \right\}.
\] (2)

To measure the changes in efficiency between periods, Caves et al. (1982) introduced the Malmquist productivity index (MPI), which is the ratio of the distance function using inputs and outputs from different periods. The MPI of period \(t\) and period \(t+1\) are defined as:

\[
\text{MPI}_t = \frac{D_t(x_t+1, y_t+1)}{D_t(x_t, y_t)}; \quad \text{MPI}_{t+1} = \frac{D_{t+1}(x_{t+1}, y_{t+1})}{D_{t+1}(x_t, y_t)}.
\] (3)

Färe et al. (1992) proposed that changes in the MPI between the two periods are the geometric mean of MPIs, which can be decomposed into two components: shifts of the frontier, which are attributable to technological progress; and movements towards the frontier, which are attributable to improvements in technical efficiency, respectively:

\[
\text{MPI}^{t,t+1} = \sqrt{\frac{D'(x_t+1, y_t+1)}{D'(x_t, y_t)} \times \frac{D'_{t+1}(x_{t+1}, y_{t+1})}{D'_{t+1}(x_t, y_t)}}
\]

\[
= \frac{D'_{t+1}(x_{t+1}, y_{t+1})}{D'(x_t, y_t)} \times \sqrt{\frac{D'(x_t+1, y_t+1)}{D'_{t+1}(x_t+1, y_t+1)} \times \frac{D'(x_t, y_t)}{D'_{t+1}(x_t, y_t)}}.
\] (4)

Distance functions can be estimated using non-parametric methods (for example, DEA) or parametric methods (for example, SFA). In this study we use the SFA to estimate the distance function. The main advantage of SFA is that it takes into account the random noise that may be associated with measurements of production. In addition, unlike the standard SFA method, the distance function SFA does not require any assumptions to be made about the objective function (for example, assumptions regarding cost-minimisation or profit-maximisation), and it can be used to take into account multi-product production processes. The SFA method does require an assumption about the functional form of the production functions (Cobb–Douglas or trans-logarithmic functions). In this study, we choose the trans-logarithmic (translog) functional form because it is able to mimic an impressive degree of flexibility (Berndt, 1991), and has been the popular choice of functional form in many previous studies (Grosskopf et al., 1997; Coelli and Perelman, 1999; Coelli and Perelman, 2000). Assuming that technological progress is represented by the

\[\text{MPI}^{t,t+1}\]
time trend \( t \), the output distance function of country \( i \) with \( K \) inputs and \( M \) outputs, under the assumption of the translog functional form, may be written as:

\[
\log(D_{Oi}) = \alpha_0 + \sum_{m=1}^{M} \alpha_m \log(y_{mi}) + \sum_{k=1}^{K} \beta_k \log(x_{ki}) + \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{M} \alpha_{mn} \log(y_{mi}) \times \log(y_{ni}) \\
+ \frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \log(x_{ki}) \times \log(x_{li}) + \sum_{k=1}^{K} \sum_{m=1}^{M} \delta_{km} \log(x_{ki}) \times \log(y_{mi}) \\
+ \sum_{m=1}^{M} \gamma_m \log(y_{mi}) \times t + \sum_{k=1}^{K} \eta_k \log(x_{ki}) \times t + \delta_1 t + \delta_1 t^2 + \varepsilon_i, \tag{5}
\]

where \( \varepsilon \) is the random error, and the functional form satisfies the constraint for homogeneity of degree one in outputs (\( \sum \alpha_m = 1 \), \( \sum \alpha_{mn} = 0 \), and \( \sum \alpha_{km} = 0 \)) and the constraint of symmetry (\( \alpha_{mn} = \alpha_{nm}, \beta_{kl} = \beta_{lk}, \) and \( \alpha_{km} = \alpha_{mk} \)).

Unfortunately, the distance function is not observed, thus equation (5) cannot be estimated as it is. In the case of a single output, one can estimate equation (5) by rearranging the distance function to the right-hand-side, and applying a standard SFA approach to decompose the composite error term (\( \varepsilon_i - \log(D_{Oi}) \)) into a random error component \( \varepsilon_i \), and an inefficiency component \( \log(D_{Oi}) \), which is assumed to follow a non-negative distribution. In the case of multiple outputs, we can apply the method proposed by Coelli and Perelman (2000), which exploits the homogeneity of degree one in outputs, selecting arbitrarily one output (for example, \( Y_{Mi} \)) as the numeraire. Recall that a function with homogeneity of degree \( \omega \) is defined as:

\[
D_O(x, \omega y) = \omega D_O(x, y) \quad \text{for} \quad \omega > 0. \tag{6}
\]

Defining one output arbitrarily as a numeraire (\( \omega = (1/y_{Mi}) \)), this transformation can be expressed as:

\[
D_O\left(\frac{X}{Y_{Mi}}\right) = \frac{D_O(X, Y)}{y_{Mi}}. \tag{7}
\]

Applying this to the translog distance function in equation (5), we can transform it to the standard SFA specification, as follows:

\[
- \log(y_{Mi}) = \alpha_0 + \sum_{m \neq M} \alpha_m \log(y_{mi}/y_{Mi}) + \sum_{k=1}^{K} \beta_k \log(x_{ki}) \\
+ \frac{1}{2} \sum_{m \neq M} \sum_{n \neq M} \alpha_{mn} \log(y_{mi}/y_{Mi}) \times \log(y_{ni}/y_{Mi}) \\
+ \frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \log(x_{ki}) \times \log(x_{li}) + \sum_{k=1}^{K} \sum_{m \neq M} \delta_{km} \log(x_{ki}) \times \log(y_{mi}/y_{Mi}) \\
+ \sum_{m \neq M} \gamma_m \log(y_{mi}/y_{Mi}) \times t + \sum_{k=1}^{K} \eta_k \log(x_{ki}) \times t + \delta_1 t \\
+ \delta_1 t^2 + \varepsilon - \log(D_{Oi}). \tag{8}
\]
Efficiency changes can then be estimated from equation (8) as the ratio of the efficiency score between the current and the reference periods, while technological changes are measured as the average of the time derivatives between periods. To take into account effects of the operational environment, we apply the technical efficiency effects model by Battese and Coelli (1995), which specifies that $m_i = z_i \sigma$, where $m_i$ is the mean of the inefficiency component $\log(D_{Oi})$ and $z_i$ is the vector of environmental variables. This procedure produces more consistent estimates than the second-stage regression approach (Coelli, 1996).

Under this specification, technical efficiency (TE) scores are defined as the exponentiation of the distance function:

$$TE_i = \exp[-\log(D_{Oi})].$$

Efficiency changes (EC) are defined as the ratio of efficiency scores between two periods:

$$EC = \frac{TE_{t+1}}{TE_t},$$

and technical changes (TC) are defined as geometric means of the time derivatives between two periods:

$$TC = \exp\left\{ \frac{1}{2} \times \left[ \delta \log(y_{Mi,t+1}) \cdot \delta \log(y_{Mi,t}) \right] \right\},$$

TFP changes (TFPC) are the product of efficiency changes and technical changes (TFPC = EC × TC). One can also calculate scale changes (SC) as the geometric means of scale efficiency between two periods:

$$SC = \exp\left\{ \frac{1}{2} \times \log \left( \frac{x_{ni,t+1}}{x_{ni,t}} \right) \times \sum_{n=1}^{N} \left[ \nu_{ni,t}SF_{i,t} + \nu_{ni,t+1}SF_{i,t+1} \right] \right\},$$

where:

$$SF_{it} = (\epsilon_{it} - 1)/\nu_{ni,t}; \quad \epsilon_{it} = \sum_{n=1}^{N} \nu_{ni,t}; \quad \text{and} \quad \nu_{ni,t} = \frac{\delta \log(y_{Mi,t})}{\delta \log(x_{ni,t})}.$$ 

This is useful when economies of scale in production are suspected. In the context of traffic safety, scale economies are determined by traffic and population density rather than the size of the traffic network, or other measures of scale such as total number of vehicles, vehicle kilometres travelled, or the size of the population (Jaarsma and van Langevelde, 2011). Investment in high-quality traffic infrastructure is arguably more feasible in more densely populated areas, and hence the density of the population and the traffic network are indicators that are likely to indicate the notion of ‘scale’ one has in mind in the context of road safety. In addition, as average travel speeds tend to be lower in high traffic density areas, the severity of crash sequelae may thereby be reduced, even if greater vehicle movement gives rise to more crashes. Finally, according to risk compensation theory (Wilde, 1976; 1982) in areas of high population density, the density of transport increases and hence people may also take more care to compensate for their increased exposure to traffic.

For comparison, we also present briefly the estimation of TFP growth and its components using DEA, which involves solving four linear programming problems using all
possible combinations of observed input–outputs and best practice frontiers in any two periods. For DEA the distance function may be specified as:

\[ D_{ij}(x_{i,j}, y_{i,j}) = \text{Min} \left\{ \theta | \lambda Y_{i,j} \geq \frac{y_{i,j}}{\theta}; \lambda X_{i,j} \leq x_{i,j}; \theta, \lambda \geq 0 \right\}, \]

where \( \theta \) is a scalar, \( \lambda \) is a vector of constants, representing the weights that apply to the input–output combinations of efficient entities (in this paper, countries, but, more commonly, firms in the productivity literature), \( X, Y \) are the matrices of inputs and outputs of all countries, and \( x, y \) are the vectors of inputs and outputs of the country being evaluated. The four linear programming problems in equation (13) assume that all firms operate at the most efficient production scale. To relax this assumption, one needs to add an additional constraint that \( \sum \lambda = 1 \) to the four linear programming problems in equation (13). Comparing results from the linear programming with and without the variable returns to scale constraint, one can measure scale efficiency growth over time.

4.0 Data

We collected data from several sources for this study. Traffic data were collected from the International Road Traffic and Accident Database (IRTAD), public health data were collected from the OECD health database (CREDES-OECD, 2007), and macroeconomic indicators were collected from the Penn World Table version 8.0 (Feenstra et al., 2013). From the IRTAD database, we selected two outcome variables (road traffic deaths and injuries per 100,000 inhabitants) and one exposure variable (number of vehicle kilometres travelled per 1,000 inhabitants). The selection of both fatalities and injuries is one of the main differences of this study compared with the literature (for example, Wegman and Oppe, 2010; Shen et al., 2012; Shen et al., 2013), where fatalities were the sole output. Missing observations on traffic injuries were imputed by applying a linear trend to the observed data.

Although ideally we would like to include indicators of the quality of trauma care systems, such data are unavailable in this collection. The OECD health collection does, however, contain other health system and health outcome indicators, including health expenditure per capita, life expectancy at birth, expected loss of life from all causes, the share of total health spending that is attributable to government, and health expenditure as a proportion of GDP. We opted to use health expenditure per capita (measured in purchasing power parity-PPP at 2005 prices) as the sole proxy for the general status of health care services. We selected the unemployment rate and CO2 emissions per capita from the Gapminder website (www.gapminder.org) as our indicators of economic activity, as economic activity may be expected to affect the rate of exposure to traffic crashes. Yet while an increase in economic activities may lead to more exposure to traffic and hence increase the probability of accidents, according to risk compensation theory, traffic users also tend to take more care at higher rates of traffic exposure. Thus, the overall effects of economic activity on traffic safety may be ambiguous. We select population density to examine its effect to the efficiency of traffic safety in the second-stage regressions, as it is expected that areas with higher population density may be more efficient producers of traffic safety, ceteris paribus. Combining data from the three sources, our final data set includes thirteen OECD countries from 1975 to 2004.
Unlike some of the previous literature (Shen et al., 2011; 2012; 2013), we do not include population independently in the input set, because all of the selected variables are expressed as ratios with population as the denominator (traffic fatalities per 100,000 inhabitants, health expenditure per capita, vehicles per capita), hence the role of population is as a normaliser. In addition, we chose an output-oriented specification to benchmark traffic safety for ease of interpretation, as the primary emphasis in the safety literature is on preventing morbidity and mortality, as opposed to conserving resources. Finally, we took the inverse of inputs and outputs so that the distance function can be estimated without further modification, because an increase inverse of traffic fatality rate is equivalent to a decrease in the traffic fatality rate, and hence is desirable. The transformed output (number of inhabitants per road traffic fatality) can be interpreted as the inverse odds of road traffic deaths. For example, the odds of a traffic death are presented as 1 : 400, while we use 400 : 1 in the analysis (that is, the inverse odds of traffic death or the odds of traffic survival).

The data in Table 1 show that the range of road traffic fatality rate in these selected OECD countries is about sixfold (from 5.4 to 33.4 deaths per 100,000 people), while the range of traffic injury is more than tenfold. Among the exposure variables, VKT show the greatest variation, with the standard deviation being greater than the mean. The descriptive statistics also show that despite large discrepancies in health expenditure per capita, countries in the sample achieve fairly similar results on health sector measures such as life expectancy at birth and the fertility rate.

Figure 1 presents visual depictions of the production possibility frontiers (PPFs) for traffic safety in 1975 and 2004, using population/traffic fatalities and population/traffic injuries as two outputs, and population/VKT and population/vehicles as two possible input proxies for traffic exposure. The PPFs in Figure 1 show that traffic safety has increased considerably over the past 30 years among the countries in this sample. Figure 1(a) shows that, in 1975, countries could, at best, reduce traffic deaths to one fatality per 80 million VKT or one traffic injury for every two million VKT. By comparison, in 2004, the lowest

<p>| Table 1 |</p>
<table>
<thead>
<tr>
<th>Variables</th>
<th>Min</th>
<th>Std.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traffic fatalities per 100,000 people</td>
<td>14.32</td>
<td>5.47</td>
<td>5.35</td>
<td>33.36</td>
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<tr>
<td>Traffic injuries per 100,000 people</td>
<td>5604.35</td>
<td>3087.79</td>
<td>1397</td>
<td>15141</td>
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<tr>
<td>Persons per vehicle</td>
<td>2.03</td>
<td>0.56</td>
<td>1.3</td>
<td>5.51</td>
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<td>Vehicle kilometres travelled (millions)</td>
<td>470637.7</td>
<td>929722.4</td>
<td>14410</td>
<td>4800000</td>
</tr>
<tr>
<td>Real GDP per capita (PPP, 2005)</td>
<td>25077.42</td>
<td>5417.23</td>
<td>15136.8</td>
<td>41540.7</td>
</tr>
<tr>
<td>Health expenditure per capita (PPP, 2005)</td>
<td>1475.91</td>
<td>909.93</td>
<td>212</td>
<td>6037</td>
</tr>
<tr>
<td>Life expectancy at birth (years)</td>
<td>76.25</td>
<td>2.2</td>
<td>71.2</td>
<td>82.1</td>
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<td>Fertility rate (child per women)</td>
<td>1.7</td>
<td>0.25</td>
<td>1.16</td>
<td>2.8</td>
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<tr>
<td>Unemployment rate (per cent)</td>
<td>7.17</td>
<td>4.03</td>
<td>0.2</td>
<td>23.9</td>
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<td>CO₂ emission/capita (kg)</td>
<td>11.08</td>
<td>4.1</td>
<td>4.94</td>
<td>21.69</td>
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<tr>
<td>Percentage of people over 65 years old</td>
<td>13.68</td>
<td>2.5</td>
<td>7.9</td>
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<td>Expected life loss from all causes (years/100,000 inhabitants)</td>
<td>5047.2</td>
<td>1219.64</td>
<td>2757</td>
<td>8377</td>
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<td>Health expenditure as a proportion of GDP</td>
<td>7.92</td>
<td>1.71</td>
<td>4.6</td>
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<tr>
<td>Population density (persons per sq. km)</td>
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<td>117.29</td>
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</tbody>
</table>
road fatality rate was one per 150 million VKT and one traffic injury per 6.3 million VKT. Figure 1(b) shows that, in 1975, the best practice countries had one traffic death for every 3,000 vehicles; while, by 2004, the highest-achieving countries had reduced this number to approximately one death per 11,000 vehicles. The number of vehicles per one traffic injury case on the frontier also increased from about 180 in 1975 to 350 in 2004. Furthermore, inefficient countries in 2004 still enjoy a level of traffic safety that was not achievable even for the best-practice countries in 1975. This is especially evident when the number of vehicles is used as the proxy measure of traffic exposure. When VKT is used as the proxy for exposure, though, the traffic safety performance of one country in 2004 is worse than that of other countries in 1975. This apparent effect may, however, be due to measurement errors in the VKT variable, as it has, historically, often been measured indirectly via, for example, fuel consumption, driver surveys, or traffic counts (Rudman, 1979; Leduc, 2008).

5.0 Results and Discussions

The SFA results show that the average traffic safety efficiency score for the OECD countries in this sample is 91 per cent, thus suggesting that currently inefficient OECD countries can improve their efficiency in traffic safety by, on average, 9 per cent (see Table 2). Expressed differently, by learning from the best-practice countries, currently inefficient countries could improve the inverse odds of traffic fatalities from the average of 8,100 to 8,829. Similarly,
the inverse odds of traffic injury may be increased from 253 to 276 at the same levels of traffic exposure and investment in health services.

The MPI shows that, on average, the total factor productivity (TFP) of traffic safety of the countries in the sample increased by 2.2 per cent per year in the study period. Countries with the fastest annual TFP growth rates include the United Kingdom (12.3 per cent) and Japan (8.2 per cent). The trend of TFP changes by countries also confirmed that the UK and Japan experienced the highest growth in the TFP of traffic safety in most years (see Figure 2). This finding is similar to that produced by Shen et al. (2013), who found that TFP growth in traffic safety of twenty-six European countries in the 2001–10 period was 20 per cent (that is, 2 per cent per year, on average). We also find that technological progress is the main contributor to TFP growth among OECD countries with the average annual growth rate of 1.55 per cent. The United Kingdom and Japan also lead the OECD countries in our sample in their technological progress in traffic safety, with average annual growth rates of 6.8 and 6.0 per cent, respectively.

Changes to economies of scale contributed 0.6 per cent to the average annual TFP growth, with the United Kingdom and Japan again achieving the fastest annual growth rates of 4.6 and 2.4 per cent, respectively. The relative positions of most countries, with respect to the frontier (representing changes in efficiency), is almost unchanged, with a slight increase of only 0.04 per cent; the United Kingdom remains one of the few countries with positive growth. Japan, by contrast, experienced a slight decline. The USA exhibits the lowest average technical efficiency at 64.7 per cent, and the USA and Finland are the only countries that experienced negative growth in all three components of TFP. One possible reason for the inefficiency of the USA is the fast rate of growth of health expenditure there by comparison with other OECD countries (White, 2007).

Table 3 presents the regression results from SFA analyses of traffic safety efficiency. The results show that basic model selection criteria improve substantially when environmental variables are taken into account. Both the Akaike Information Criteria (AIC) and Bayesian
Information Criteria (BIC) decline, and the log likelihood increases when moving from the model that does not account for environmental variables (the error component model) to the specification that includes these variables (the technical efficiency or 'TE effects' model). The likelihood ratio (LR) test also shows that one cannot reject, from the error component model, the null hypothesis that there is no efficiency component. On these grounds, the TE effects model is thus preferred, and the remainder of the paper focuses on the results obtained from that model.

The estimates from the TE effects model suggest that traffic exposure has no statistically significant effect on traffic safety, but it has the expected, positive, signs. One possible explanation for this result may be technological improvements in vehicles and traffic infrastructure over time. The parameter on health expenditure is statistically significant at 5 per cent level and has the expected, positive sign. In particular, a 1 per cent increase in health expenditure per capita is associated with an estimated 0.15 per cent increase in the inverse odds of traffic deaths.

For comparative purposes, we produce efficiency estimates using the rate of vehicle ownership as a proxy for traffic exposure. The basic model selection criteria (BIC and AIC) of this estimate are better than that of the model where VKT is used as a proxy for exposure (see Table 3, last column). The signal-to-noise ratio (that is, parameter $\lambda = \delta_d/\delta_e$ in Table 3) of this estimate (0.095) is also higher than that of the original model (0.064). One noticeable difference in the results obtained from this model is that exposure ($x_1$) is statistically significantly and positively associated with a traffic fatality rate with the elasticity of 0.84, which is the highest magnitude elasticity among the selected inputs. The other parameter estimates are very similar to those reported previously.
Table 3 also shows that all three environmental variables are statistically significantly associated with the efficiency of traffic safety. The negative sign of the estimated parameter on the unemployment rate is contrary to expectations: an increase in the unemployment rate should, theoretically, be associated with less traffic exposure and hence an increase in traffic safety efficiency. If, however, risk compensation outweighs the benefits of reduced exposure, such a result would arise. The expected positive sign of the unemployment parameter is, however, obtained when vehicle ownership is used as the exposure measure. Similarly, the positive sign of parameter for CO₂ emissions per capita is contrary to expectations: an increase in CO₂ emissions may be expected to be associated with increased industrial activities and exposure. Once again, this result is explicable according to risk compensation theory if people take more care as the perceived level of risk increases, thereby improving road traffic safety. Scale economies in traffic safety which may be indicated by traffic density, as suggested by Jaarsma and van Langevelde (2011), may also contribute to this finding. For example, road infrastructure, policing and trauma

<table>
<thead>
<tr>
<th>Variables</th>
<th>Using VKT as exposure(^a)</th>
<th>((\text{TE effects model}))</th>
<th>Using vehicles as exposure(^b)</th>
<th>((\text{TE effects model}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>−0.040 (0.031)</td>
<td>−0.011 (0.033)</td>
<td>0.008 (0.036)</td>
<td></td>
</tr>
<tr>
<td>Log(x1)</td>
<td>0.019 (0.012)</td>
<td>0.015 (0.013)</td>
<td>(0.841 (0.077))</td>
<td></td>
</tr>
<tr>
<td>Log(x2)</td>
<td>−0.093 (0.048)</td>
<td>0.152 (0.057)</td>
<td>(0.221 (0.052))</td>
<td></td>
</tr>
<tr>
<td>Log(x3)</td>
<td>(−0.064 (0.025))</td>
<td>(−1.127 (0.023))</td>
<td>(−0.193 (0.024))</td>
<td></td>
</tr>
<tr>
<td>Log(x1)(^2)</td>
<td>(−0.026 (0.011))</td>
<td>(−0.024 (0.009))</td>
<td>(−0.298 (0.613))</td>
<td></td>
</tr>
<tr>
<td>Log(x1) × log(x2)</td>
<td>−0.009 (0.049)</td>
<td>−0.018 (0.047)</td>
<td>(−0.772 (0.306))</td>
<td></td>
</tr>
<tr>
<td>Log(x1) × log(x3)</td>
<td>0.008 (0.033)</td>
<td>−0.001 (0.031)</td>
<td>0.183 (0.105)</td>
<td></td>
</tr>
<tr>
<td>Log(x2)(^2)</td>
<td>(1.184 (0.128))</td>
<td>(1.036 (0.127))</td>
<td>(1.153 (0.119))</td>
<td></td>
</tr>
<tr>
<td>Log(x2) × log(x3)</td>
<td>(0.328 (0.128))</td>
<td>(0.478 (0.119))</td>
<td>0.180 (0.093)</td>
<td></td>
</tr>
<tr>
<td>Log(x1) (\times t)</td>
<td>−0.001 (0.003)</td>
<td>−0.002 (0.003)</td>
<td>(0.065 (0.014))</td>
<td></td>
</tr>
<tr>
<td>Log(x2) (\times t)</td>
<td>(−0.066 (0.023))</td>
<td>(−0.77 (0.022))</td>
<td>(−0.072 (0.020))</td>
<td></td>
</tr>
<tr>
<td>Log(x3) (\times t)</td>
<td>(−0.065 (0.009))</td>
<td>(−0.48 (0.009))</td>
<td>(−0.63 (0.009))</td>
<td></td>
</tr>
<tr>
<td>Trend ((t))</td>
<td>(0.033 (0.003))</td>
<td>(0.016 (0.004))</td>
<td>(0.026 (0.004))</td>
<td></td>
</tr>
<tr>
<td>(t^2)</td>
<td>(0.004 (0.002))</td>
<td>(0.005 (0.002))</td>
<td>(0.006 (0.001))</td>
<td></td>
</tr>
<tr>
<td>(δ)</td>
<td>(0.063 (0.004))</td>
<td>(0.015 (0.003))</td>
<td>(0.019 (0.003))</td>
<td></td>
</tr>
<tr>
<td>(δt)</td>
<td>(0.247 (0.007))</td>
<td>(0.235 (0.007))</td>
<td>(0.200 (0.007))</td>
<td></td>
</tr>
<tr>
<td>(λ)</td>
<td>(0.254 (0.008))</td>
<td>(0.064 (0.008))</td>
<td>(0.095 (0.008))</td>
<td></td>
</tr>
<tr>
<td>LR test ((p-val))</td>
<td>(−0.00002 (0.964))</td>
<td>37.55 (0.000)</td>
<td>41.49 (0.000)</td>
<td></td>
</tr>
<tr>
<td>Unemployment</td>
<td>−0.028 (0.015)</td>
<td>(0.100 (0.034))</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CO₂/capita</td>
<td>(0.730 (0.102))</td>
<td>(0.412 (0.098))</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population density</td>
<td>(0.061 (0.011))</td>
<td>(0.092 (0.012))</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(\text{Note: Output is population/traffic fatalities.}\)

\(^{a}\text{x1} = \text{population/VKT}; \text{b}\text{x1} = \text{population/vehicles}; \text{x2} = \text{health expenditure/population}; \text{x3} = \text{output2/}

\text{output1 = (population/injuries)/(population/fatalities) = fatalities/injuries.}\)

Robust standard errors are in parentheses: \(* p < 0.1; \*\* p < 0.05; \*\*\* p < 0.01.\)
care are also often better in areas of highly traffic density (for example, cities), and may lead to reductions in traffic fatalities.

Since the parameters of environmental variables in Table 3 are difficult to interpret directly, we calculate the marginal effects of these variables. Since the marginal effect depends on the value of these variables, we calculate the marginal effects based on all values of CO$_2$ and population density, and illustrate their histograms in Figure 3. The results show the effect of a 1 per cent increase in the unemployment rate on the efficiency of traffic safety ranges from $-0.3$ to $0$ percentage points, while that of CO$_2$ per capita and population density are $(0.0, 0.8)$ and $(-0.04, 0.06)$, respectively. It is interesting that the marginal effects of population density include some negative values (that is, suggesting that increases in population density lead to decreases in the efficiency of traffic safety). The relative effects of perceived safety and risk compensation perhaps also contribute to this outcome. However, on average, an increase of one tonne of CO$_2$ emission per capita and one person per km$^2$ in population density is associated with an increase of traffic safety efficiency by 0.42 and 0.03 percentage points, respectively. By contrast, a 1 per cent reduction in the unemployment rate is associated with a 0.02 percentage point increase in traffic safety efficiency.

To explore the sensitivity of results, we also estimated the TFP growth of traffic safety using combinations of methods (SFA and DEA), choices of exposure (VKT and vehicles),
and numbers outputs (fatalities and injuries, and fatalities only). While the selection of DEA as a method and number of vehicles as an exposure is to test for sensitivity to measurement-errors in the data, we selected fatalities as the sole output to test for the hypothesis that injuries data may not be reliable (for example, due to under reporting of minor injuries and differences in definitions of injuries among countries). The cumulative TFP growth, presented in Figure 4(a), suggests that all such models produce evidence of a clear trend in TFP growth in traffic safety over the past 30 years, but the DEA results exhibit substantial differences. The estimates obtained from SFA are sandwiched by those obtained by DEA. For instance, the most rapid TFP growth estimate — a tenfold increase — was obtained from DEA using VKT as the exposure measure and fatalities as the single output measure. This is indicated by the plot labelled DEA-VKT-1 in Figure 4(a). The lowest TFP growth estimate — a 1.3-fold increase — was also obtained by DEA using numbers of vehicles as the exposure measure, and both fatalities and injuries as the output measures. These estimates are indicated by the plot labelled DEA-VEH-2 in Figure 4(a). The SFA results produce faster TFP growth estimates when vehicles are used as the exposure measure, while DEA estimates using VKT as the exposure measure also produce faster TFP growth estimates. Based on the basic guide of empirical frontiers in Figure 1 — where the frontiers in 2004 shifted further from those of 1975 when vehicles were used as the exposure measure — we believe that the model that uses vehicles as the exposure measure should predict higher TFP growth, as the SFA results suggest. Also, the correlation matrix of the TFP growth estimates produced by various models shows that the TFP growth estimates from two of our SFA models have a correlation coefficient of 0.83, while the DEA predictions show considerably weaker correlations, both with each other and with the SFA results.

We believe that variations in the DEA results are likely due to its vulnerability of measurement errors, which are known to affect VKT data. As can be seen in Figure 4(b), the index of annual average VKT fluctuates quite considerably, while other

Figure 4
Cumulative TFP Growth and Input–output Indexes

(a) Cumulative TFP growth

(b) Input–output Index
inputs and outputs exhibit fairly smooth trends. Among the inputs, health expenditure experienced the fastest growth level: health expenditure in 2004 was, on average, seven times its level in 1975. Recall that VKT is often measured indirectly via fuel consumption, road counts, and driver surveys (Rudman, 1979; Leduc, 2008), and hence applications of the non-parametric approach to measure traffic efficiency using VKT may suffer bias due to measurement error. One may argue that this issue could be mitigated using a bootstrap procedure such as the algorithm developed by Simar and Wilson (1998), but a bootstrap procedure can only test the robustness of results due to sampling variability, not measurement error (Coelli et al., 2005, p. 202). Fortunately, the DEA studies in the literature covered a relatively short time frame, and hence possibly had fewer measurement errors.

The average TFP growth by countries, presented in Table 4, confirms that the DEA results predict both the highest TFP growth (when VKT is used as the exposure measure) and the lowest TFP growth (when vehicles are used as the exposure measure). SFA produces consistent results, suggesting that the United Kingdom, Japan and Canada are the best performers, irrespective of which exposure measure or number of outputs is used. Taking both DEA and SFA results together, the United Kingdom appears to have been the highest achiever in traffic safety efficiency over the past 30 years.

The detailed SFA results when fatalities are used as the sole output are presented in Table 5. The results of the two specifications are consistent: the main result is that exposure is a statistically significant determinant of traffic fatalities, with the elasticity of 0.9 (when vehicles are used as exposure) and 0.6 (when VKT is used as exposure). The results also suggest that unemployment is positively associated with the efficiency of traffic safety. But the model selection criteria (AIC and BIC) suggest that two-output models are preferred.
One advantage of DEA is that it can provide information about peers (efficient countries that serve as efficiency ‘role models’ that inefficient countries with similar input–output structures may learn from to improve efficiency). We illustrate this by constructing a peer network for 1975 (Figure 5(a)) and 2004 (Figure 5(b)). The arrows in Figure 5 point from inefficient countries to their efficient peers, and darker (lighter) circles indicate that the country concerned acts as a peer for many (fewer) inefficient countries. Similarly, the density of the arrows represents the strength by which the input–output structure of an efficient country is relevant to its inefficient peers. Finally, a semi-circular arrow indicates a peer self-reference, meaning that it has no more efficient peer and hence it is its own benchmark.

In 1975, Finland was technically efficient, but its input–output structure was so unique that no other country was proximate enough to learn from it.\(^3\) The peer network in 2004 shows that the United Kingdom and Sweden remain influential, but Sweden has greater peer weights than it did in 1975. Interestingly, the USA and Finland became influential with five and four peers, respectively. However, Denmark, New Zealand, and Spain became ‘efficient by default’ as they had no peers, despite being efficient. Overall, this information is in line with previous studies (Wegman and Oppe, 2010; Shen \textit{et al.}, 2012; Shen \textit{et al.}, 2013) that suggest that the United Kingdom and Sweden are among the best-practice

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\( \text{Table 5} \)

\textit{SFA Regressions (Use Fatalities as Output)}

<table>
<thead>
<tr>
<th>Variables</th>
<th>Using vehicles as exposure(^a)</th>
<th>Using VKT as exposure(^b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>***0.202 (0.040)</td>
<td>0.220 (0.423)</td>
</tr>
<tr>
<td>Log(x1)</td>
<td>***0.912 (0.079)</td>
<td>***0.060 (0.014)</td>
</tr>
<tr>
<td>Log(x2)</td>
<td>−0.146 (0.089)</td>
<td>−0.316 (0.505)</td>
</tr>
<tr>
<td>Log(x1)²</td>
<td>−2.878 (0.728)</td>
<td>−0.024 (0.019)</td>
</tr>
<tr>
<td>Log(x1) × log(x2)</td>
<td>−1.383 (0.330)</td>
<td>−0.080 (0.052)</td>
</tr>
<tr>
<td>Log(x2)²</td>
<td>−0.566 (0.373)</td>
<td>−0.569 (0.875)</td>
</tr>
<tr>
<td>Log(x1) × t</td>
<td>***0.067 (0.017)</td>
<td>0.005 (0.004)</td>
</tr>
<tr>
<td>Log(x2) × t</td>
<td>−0.003 (0.021)</td>
<td>0.031 (0.065)</td>
</tr>
<tr>
<td>Trend ( (t) )</td>
<td>***0.052 (0.006)</td>
<td>0.050 (0.031)</td>
</tr>
<tr>
<td>( t^2 )</td>
<td>0.002 (0.001)</td>
<td>−0.002 (0.004)</td>
</tr>
<tr>
<td>( \delta u )</td>
<td>**0.115 (0.048)</td>
<td>0.179 (0.517)</td>
</tr>
<tr>
<td>( \delta v )</td>
<td>**0.239 (0.013)</td>
<td>*0.255 (0.142)</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>***0.482 (0.059)</td>
<td>0.699 (0.658)</td>
</tr>
</tbody>
</table>

| Unemployment | ***0.384 (0.052) | ***0.294 (0.057) |
| CO₂/capita   | −0.156 (0.183)   | −0.337 (1.239)   |
| Population density | *0.045 (0.015) | 0.008 (0.070) |

AIC: 55.817 \hspace{1cm} 141.591  \hspace{1cm} BIC: 115.309 \hspace{1cm} 201.083  \hspace{1cm} Log likelihood: −12.909 \hspace{1cm} −55.796

Note: Output is population/traffic fatalities.

\( ^a x_1 = \text{population}/\text{vehicles} \); \( ^b x_1 = \text{population}/\text{VKT}, x_2 = \text{health expenditure}/\text{population} \).

Robust standard errors are in parentheses: \( * p < 0.1; ** p < 0.05; *** p < 0.01 \).

---

\(^3\)This characteristic is referred to in the efficiency analysis literature as ‘efficient by default’. For more details, see, for example, Coelli \textit{et al.} (2005).
traffic safety countries in Europe. The appearance of the United Kingdom as a ‘star’ country is also consistent with the SFA results, which suggest that this country has the highest growth in TFP and its components. We found that, in 1975, the United Kingdom and Sweden played the role of peer for eight other inefficient countries (see Figure 5(a)). However, the United Kingdom was a more influential peer because its input–output structure had higher weights (as indicated by the denser arrows that point toward it) than Sweden’s structure. Other efficient countries in 1975 included Spain and New Zealand, but they were much less influential, as only a couple of countries shared similar input–output configurations.

6.0 Conclusions

This paper has examined productivity growth in traffic safety in thirteen OECD countries in the 1975–2004 periods, using distance function approach and latent risk theory. Our preferred method — SFA — suggests that TFP in traffic safety of OECD countries has increased by approximately 2 per cent per year over the last three decades. The results also show that technological progress is the main driver of TFP changes. This finding is in line with current results of DEA study by Shen et al. (2013) for European countries. We found that OECD countries can, on average, improve their traffic safety efficiency by 9 per cent by learning from the best practice countries in the sample. The DEA results exhibit substantial variation, which we suspect are due to effects of errors-in-variables of the exposure variables, especially vehicle kilometres travelled. Thus, the current paper provides not only some insight into the efficiency of road safety developments over a three-decade period, but also a robustness check for DEA studies.

The data used in this study were sufficient for the purposes of this work for only thirteen OECD countries, and only up until 2004. Future research would extend the data coverage both in the cross-section and time-series in order to produce a more comprehensive picture.
of efficiency in road traffic safety. Since the accidents and their outcomes are undesirable, we believe that it is feasible to apply a cost-function approach to the measurement of efficiency of traffic safety for sensitivity analysis. The application of Bayesian SFA (Griffin and Steel, 2007) could also provide an additional test of the robustness of the findings reported here.

References


