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Factors associated with the relationship between non-fatal road injuries and economic growth

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ABSTRACT

This study reports the results of an empirical analysis of the Kuznets curve relationship between non-fatal road injuries and per-capita income. This relationship indicates that the number of road deaths increases with increasing per-capita income at lower income levels, but decreases once it has exceeded a threshold level. We apply a fixed effects negative binomial regression analysis on a panel of 90 countries over the period of 1963–2009. Results indicated evidence of an inverted U-shaped relationship between economic growth and non-fatal road injuries for both less developed and highly developed countries. Results also indicated that the turning point is higher in less developed countries than in higher developed countries. The evidence presented in this study suggests that improvements in road infrastructure, the quality of regulatory institutions, and increase in the use of safer transport modes will help reduce non-fatal road injuries.

1. Introduction

The relevance of the relationship between economic growth and road safety has long been recognized. However, it has been the impact of economic growth on road deaths that has attracted the most attention (Wintemute, 1985; Söderlund and Zwi, 1995; Beeck et al., 2000; Kopits and Cropper, 2005). Recently, numerous studies have shown that there is an inverted U-shaped relationship between road deaths and economic growth (Bishai et al., 2006; Beeck et al., 2000; Moniruzzaman and Andersson, 2008). That is, road deaths increase at lower income levels, but decrease once the number has exceeded a threshold level. This relationship is also known as the Kuznets curve relationship, which existed between income inequality and per-capita income (Kuznets, 1955). It is important to understand how economic growth affects road safety because road safety concerns could lead to a primary road safety policy agenda. This relationship has been explained by several studies to be the result of changes in the fundamental development of a country. This includes changes in variations in rates among vulnerable non-motorized road users (Paulozzi et al., 2007), advances in medical services (Law et al., 2009, 2011; Noland, 2003), the quality of political institutions (Anbarci et al., 2006; Law et al., 2011), income equality (Anbarci et al., 2009) and road safety policies (Law et al., 2009).

The Kuznets curve hypothesis for road safety can be supported by three theoretical explanations: the scale of economic activities, changes in vehicle composition, and a surge in demand for better road safety as per-capita income rises (Law et al., 2009). The Kuznets curve hypothesis contends that the number of road deaths increases initially as a country's economy develops, owing to the fact that the growth of a country's economy is accompanied by a corresponding surge in demand for transportation services (Dargay and Gately, 1999). Several previous studies have found that one of the contributing factors to the increase in road crashes and injuries is the growing number of vehicles per-capita (Bishai et al., 2006; Kopits and Cropper, 2005).

The composition effect depicts the change in vehicle composition as a country's economy grows. This involves a change from low-threat and high-risk transport modes (such as pedestrians and bicyclists) to high-threat and low-risk motorized vehicles (Bhalla et al., 2007). In the initial stage of economic development, the total road death risk initially increases for the reason that an increase in the number of motorized vehicles can pose an increasing threat to the predominantly more vulnerable transport modes. Nevertheless, at higher levels of economic development, when a majority of the commuting population are less vulnerable motor vehicle occupants, there is an increase in the number of motor vehicles causing a reduction in the total road death risk. This indicates an inverted U-shaped relationship between road deaths and income.

The abatement effect is the result of road death risk alleviation

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measures, which reflects both supply side and demand influences. On the demand side, at low income levels, people are less capable to invest in road safety, even though there is a demand for it, resulting in low abatement. Nonetheless, as the level of income rises, people pay greater attention to road safety and they can afford higher-cost road safety enhancement measures, enabling more commuters to switch to lower-risk modes of transport. On the supply side, at low levels of income, society is unable to afford sufficient resources to establish the social institutions needed to regulate road safety interventions. With a higher income level, abatement efforts become more substantial because more resources are available to invest in road safety. Therefore, road safety regulatory institutions become more effective. This supply side of abatement, together with the demand side mentioned above, is expected to yield a declining relationship between road deaths and income.

Bishai et al. (2006) found that at higher income levels, an increase in per-capita income appears to reduce road deaths, but does not reduce road crashes and injuries. However, their analysis does not explain the underlying mechanism that drives these relationships. In addition, their analysis applied a fixed effect ordinary regression, which is inappropriate to model count data. Thus, the objective of this study is to understand how economic growth affects non-fatal road injuries and what factors underlie this relationship.

The analysis presented in this study examines the relationship between non-fatal road injuries and economic growth, spanning a 47-year period. Several explanatory variables, which are related to the fundamental development of a country, are included to account for this relationship. In particular we include motorization level, the urban-to-rural population ratio, the percentage of the population below the age of 15 and over the age of 64, democracy level, political stability, and adult alcohol consumption rate.

2. Methodology

The analysis of count data, such as non-fatal road injuries, often does not follow the underlying assumption of normality, limited to non-negative integer values and the distribution is highly skewed (Gardner et al., 1995; Cameron and Trivedi, 1998). Therefore, the conventional ordinary linear regression may not be appropriate to analyze this sort of data (Long, 1997). Transformation of the data may not yield normally distributed data. Furthermore, this may cause difficulty in interpreting the regression coefficients because the transformed data are not estimated on the original scale (Byers et al., 2003) and the accuracy of the estimated results is questionable (Chang and Pocock, 2000).

In view of the above facts, the Poisson and the negative binomial regression methods are frequently used to model count data. However, the selection of the Poisson or the negative binomial regression is based on the difference between mean and variance. The Poisson regression model assumes the mean is equal to variance, also known as equidispersion. If this assumption is violated (overdispersion), the Poisson model will produce consistent coefficient estimates, but standard errors will be underestimated (Cameron and Trivedi, 1998; Winkelmann, 1997).

The log-likelihood ratio test is used to test the hypothesis that the variance and mean is equal, which indicates equidispersion. Rejection of the null hypothesis implies that the negative binomial is more appropriate than the Poisson regression. In the models estimated in this study, the log-likelihood ratio test showed that the null hypothesis can be rejected at 5% level of significance, implying that the negative binomial regression model is the preferred model.

The present study used the design that combine longitudinal and cross-sectional methods. The fixed effects negative binomial regression, derived by Hausman et al. (1984), is employed in this study. The fixed effects model assumes that the country specific intercept is correlated with explanatory variables. The first advantage of this model is that it can cancel out the dispersion parameters and account for heterogeneity in the data[1]. The second advantage of this model is the country specific intercepts are able to take into account differences in accident data derivation due to different sources of accident data used[2].

Alternatively, another method known as random effects model assumes that the inverse of the over-dispersion parameter is distributed as a beta distribution. The assumption applied in this model is that country specific effects as part of the error term. Another assumption is that the country specific effect is uncorrelated with the explanatory variables, which is often unrealistic (Baltagi, 2001; Wooldridge, 2000).

The choice between fixed and random effects model is based on the Hausman test (Baltagi, 2001). The null hypothesis for the test is the country specific intercept is uncorrelated with other explanatory variables. Rejection of the null hypothesis indicating fixed effects model is more appropriate. For the data analyzed here, it was found that the more appropriate effect for all models was the fixed effect[3].

An offset variable is included in the analysis to normalize the effect of risk exposure on non-fatal road injuries. This is necessary because a country with a higher level of risk exposure should experience more road crashes. The offset variable is specified as the logarithm of a measure of risk exposure in the equation and can be written as

$$\log(\mu_{it}) = \alpha_i + \beta x_{it} + \log(E_{it}) \quad (1)$$

where μ_{it} denotes the expected number of non-fatal road injuries, E_{it} represents an index of risk exposure, α_i is the country specific intercept, x_{it} is a vector of covariate which describes the characteristics of an observation unit i during a given time period t, β is the model parameters. This equation can be rewritten as

$$\log(\mu_{it}) - \log(E_{it}) = \alpha_i + \beta x_{it} \quad (2)$$

and then

$$\log(\mu_{it}/E_{it}) = \alpha_i + \beta x_{it} \quad (3)$$

The coefficient for the explanatory variables is interpreted as effects on rates rather than a count. From Eq. (1), the expected number of non-fatal road injuries is given by $\mu_{it} = E_{it}\exp(\alpha + \beta x_{it})$. This means that the expected number of non-fatal road injuries is proportional to the level of risk exposure.

3. Data

The empirical analysis in this paper uses an unbalanced[4] panel dataset which consists of a total of 1653 observations from 90 countries (both less developed and highly developed countries) for the period between 1963 and 2009. These countries were selected based on the availability of data on all explanatory variables for at least three years. The sample is divided into two groups:- less developed and highly developed countries, according to the definition of the International Monetary Fund (IMF) (2014) and the

[1] This is done by conditioning on the total number of non-fatal road injuries that occurred within each country during the study period.

[2] Most of the developed countries use hospital data as the source, while in developing countries, it is mostly taken from police.

[3] The Hausman test rejects the null hypothesis at 5% significance level.

[4] Some data are missing for some countries and years.