Road Traffic Safety

Subjects: Sociology
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This paper attempts to examine whether socioeconomic volatility produces differentiated effects on road traffic accident indicators. Adopting the Autoregressive distributed lag error-correction model (ARDL-ECM) , this paper explores the long-term equilibrium and short-term interactions between five common economic indicators, namely, average salaries (AS), employment (EM), unemployment (UE), total mileage of highway (TMH), and private vehicle ownership (PVO), as well as road traffic-related indicators including the number of road traffic accidents (RTA), injuries (IN), fatalities (FA), and direct economic losses (DEL), using data of road traffic accidents spanning from 1999 to 2018 in China. The study found that all economic indicators except average salaries showed a long-term equilibrium with road traffic accident indicators. The Granger causality test showed that, over the short term, an increase in employment could lead to an increase in injuries, and an increase in private vehicle ownership could cause a rise in fatalities. This study demonstrates that the volatility in economic indicators indeed produces differentiated effects on road traffic accident indicators, providing a theoretical basis for improving road safety performance and formulating relevant policies.

Keywords: road traffic safety ; macroeconomic ; injuries ; fatalities ; ARDL-ECM model

1. Introduction

Road safety performance represents one of the most fundamental indicators for the maturity of a motorized society across the world [1]. Despite people's longtime commitment to higher road safety performance and lower traffic accident rates, traffic accidents are still one of the major public safety issues. Each year, millions of people are injured and more than 1.3 million are killed in road traffic accidents around the world [2].

Studies show that macroeconomic factors are closely related to road traffic accidents [3][4]. In this area, a large body of scholarly research has been conducted in order to determine the specific economic indicators influencing road traffic accidents. In particular, gross domestic product (GDP) per capita as an important indicator measuring the level of regional economic development has drawn extensive research attention [5]. By comparing GDP per capita and traffic accident fatality rates in 27 European countries, George Yannis [6] found that GDP per capita was positively correlated with traffic accident fatality rate and increased GDP per capita would lead to a rise in the traffic accident fatality rate. A study conducted by Douglas J. Wiebe [7] concluded that GDP growth resulted in a rise in the number of fatalities caused by road traffic accidents. Iman Dadgar [8] examined the relationship between GDP and traffic accident fatality rates in 18 Organisation for Economic Co-operation and Development (OECD) member countries, finding that for every $1000 increase in GDP per capita, the traffic fatality rate increased by 0.58% over the short term and 1.59% over the long term. Empirical analyses focusing on Spain [9] and other European regions [10] also found that changes in GDP per capita affect road traffic accidents.

Another intensively researched indicator that is closely associated with economy is the unemployment rate. By analyzing the traffic accident data of Queensland in Australia spanning from 1958 to 2007, Son Nghiem [11] found that for every 1% decrease in the unemployment rate, fatalities caused by traffic accidents dropped by 0.2%. A study from Virginia found that every 1% increase in the unemployment rate was associated with a reduction of as many as around 2500 traffic accidents [12]. Furthermore, the Kuznets hypothesis regarding road traffic accidents has also received intensive scholarly attention [13][14]. In particular, the Kuznets relationship between traffic accidents and per capita income has been repeatedly demonstrated [15][16][17], which posits that traffic accidents exhibit a growing trend in the early stage of economic growth but will be effectively inhibited as economic growth continues and improvements in policy and infrastructure are achieved. In the meantime, there have also been studies showing that economic volatility affects government budgets, which in turn leads to changes in road traffic accidents [18][19][20]. Subject to the effect of multiple economic crises over recent years, the cyclical interactions between economic volatility and road traffic accidents have gained broader attention, and factors like alcohol taxes [21] and vehicle miles traveled [22] have also been proven to exert different degrees of impact on road traffic accidents.

Despite the extensive attention paid to the relationship between macroeconomic factors and road traffic accidents, most current studies are concentrated on developed countries or regions [23][24], and very few studies have focused on cases from developing countries. In reality, most accidents associated with fatalities and injuries occur in low- and middle-income countries [25]. A report published by the World Health Organization (WHO) suggests that no low-income country had reduced the number of road traffic deaths from 2013 to 2016 [2]. This research selects China-specific data of road traffic accidents spanning two decades, with a view of filling in the blank of this type of research by providing a case pertaining to developing countries.

2. Results and Discussion

2.1. Unit Root Tests

The augmented Dickey–Fuller (ADF) [26] and Phillips–Perron (PP) [27] tests were selected in this study. As listed in **Table 1**, the results of the ADF test show that all of the series conform to *I*(0) or *I*(1), and the results of the PP test show that all variables conform to *I*(1) except private vehicle population and average salaries. The results of the PP test allow us to apply any method of cointegration tests as all of the series fit *I*(1). However, the results of the ADF test indicate that all of the series are integrated at *I*(0) or *I*(1); therefore, only the ARDL bound cointegration test can be applied.

Table 1. Results of the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests.

Variable	ADF Test						PP Test					
	Level			First Difference			Level			First Difference		
	t-Value	*p*	*I*(0)	*t*-Value	*p*	*I*(1)	*t*-Value	*p*	*I*(0)	*t*-Value	*p*	*I*(1)
RTA	−5.9871	0.0002	YES	−2.7375	0.0112	YES	−0.5854	0.4503	NO	−3.0986	0.0040	YES
IN	−5.0755	0.0022	YES	−809.0152	0.0001	YES	−3.2998	0.0963	NO	−3.3711	0.0021	YES
FA	−0.9856	0.2781	NO	−2.9305	0.0059	YES	−2.3419	0.3943	NO	−2.8792	0.0066	YES
DEL	−3.0905	0.0466	YES	−2.6530	0.0111	YES	−0.4987	0.4866	NO	−2.6783	0.0105	YES
EM	−2.1425	0.2325	NO	−7.8469	0.0004	YES	4.7709	1	NO	−3.0781	0.0042	YES
UE	−5.6648	0.0032	YES	−28.7953	0.0001	YES	−10.2385	0	YES	−1.7892	0.0706	YES
TMH	−4.5323	0.0045	YES	−28.3829	0.0001	YES	−2.1153	0.2412	NO	−3.8421	0.0007	YES
PVO	−3.0419	0.0499	YES	−1.9058	0.6077	NO	1.3783	0.9999	NO	−2.5041	0.3222	NO
AS	−1.9444	0.306	NO	−10.9525	0.0001	YES	−3.9072	0.0085	YES	−1.8279	0.0654	NO

2.2. ARDL Bound Cointegration Test

We used the ARDL bound cointegration test to examine the existence of a cointegration relationship among macroeconomic factors and road traffic accident indicators. The chosen lag length was based on the Akaike information criterion (AIC). AIC displays superiority over other criteria because it exhibits better small sample properties [28]. The results of the cointegration test shown in **Table 2** confirm that long-run cointegration exists among *ln*TE, *ln*TU, *ln*TMH, *ln*PVO, and road traffic accident indicators. However, the cointegration relationship between *ln*AS and road traffic accident indicators is uncertain, because the value of the bound test F-statistic is 3.3262, which is between the upper and lower critical bounds. A study of traffic accidents from Hong Kong [29] also found that the impact of GDP on traffic accidents was ambiguous.

Table 2. Results of ARDL bound testing.

Model	Lag Length Based on AIC	Bound Test F-Statistics	Significance	Lower *I*(0) Bound	Upper *I*(1) Bound
*ln*AS = *f*(*ln*RTA, *ln*IN, *ln*FA, *ln*DEL)	ARDL (1, 2, 2, 2, 1)	3.3262	5%	3.05	3.97
*ln*EM = *f*(*ln*RTA, *ln*IN, *ln*FA, *ln*DEL)	ARDL (1, 0, 1, 2, 2)	163.5342	1%	3.74	5.06
*ln*UE = *f*(*ln*RTA, *ln*IN, *ln*FA, *ln*DEL)	ARDL (1, 2, 1, 1, 1)	8.3385	1%	3.81	4.92

Model	Lag Length Based on AIC	Bound Test F-Statistics	Significance	Lower I(0) Bound	Upper I(1) Bound
*ln*TMH = *f*(*ln*RTA, *ln*IN, *ln*FA, *ln*DEL)	ARDL (1, 2, 2, 2, 2)	74.7924	1%	3.07	4.44
*ln*PVO = *f*(*ln*RTA, *ln*IN, *ln*FA, *ln*DEL)	ARDL (2, 2, 0, 1, 0)	5.9826	1%	3.07	4.44

2.3. Estimation of Long- and Short-Run Dynamics

The long-run and short-run dynamics for macroeconomic factors and road traffic accident indicators in China were estimated using the ARDL and ECM model. The results of long-run estimations are shown in **Table 3**, and short-run estimations are shown in **Table 4**.

Table 3. Long-run estimations.

Dependent Variables Independent Variables	*ln*EM		*ln*UE		*ln*TMH		*ln*PVO	
	Lag Order (1, 0, 1, 2, 2)		Lag Order (1, 2, 1, 1, 1)		Lag Order (1, 2, 2, 2, 2)		Lag Order (2, 2, 0, 1, 0)	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
*ln*RTA	−0.0847 ***	−7.6256	0.3954 **	2.8726	−1.1212 ***	−4.2545	12.4637	0.8872
*ln*IN	0.1196 ***	3.9201	−0.5492 *	−2.4010	−1.8217 **	−3.8434	−18.4985	−1.2762
*ln*FA	−0.1454 ***	−4.7967	0.223	1.2596	3.3855 ***	10.4211	14.5688 *	1.8458
*ln*DEL	0.0314 ***	10.2691	−0.1251 **	−2.4603	0.4314 ***	4.8703	−6.3795	−0.9322
T			0.0154 ***	5.5707				

*, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.

Table 4. Short-run estimations.

Independent Variables Dependent Variables	*ln*EM		*ln*UE		*ln*TMH		*ln*PVO	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
C	2.7694 ***	35.9001	6.5080 ***	9.6169				
D(*ln*POV(-1))							0.6930 ***	13.7840
D(*ln*RTA)			−0.0692	−0.7199	0.5997 ***	9.1133	0.4609 ***	6.3802
D(*ln*RTA(-1))			−0.1678 **	−3.5285	−0.4996 ***	−4.7462	−0.1360 ***	−4.7498
D(*ln*IN)	0.0184 ***	17.6991	−0.1543	−1.7276	−1.2031 ***	−16.5300		
D(*ln*IN(-1))					0.7869 ***	9.4150		
D(*ln*FA)	−0.0004	−0.2937	−0.1354	−1.6486	0.3029 ***	5.0018	0.1680 **	2.5484
D(*ln*FA(-1))	0.0118 ***	9.6067			−0.8598 ***	−10.3410		
D(*ln*DEL)	0.0035 ***	6.0647	0.0204	0.4391	0.0760 *	2.3187		
D(*ln*DEL(-1))	−0.0032 ***	−5.7597			−0.2752 ***	−7.1043		
ECM(-1)	−0.2296 ***	−35.8457	−0.8614 ***	−9.5772	−0.7356 ***	−25.9448	−0.0216 ***	−6.5733

*, **, and *** indicate the significance level at 10%, 5%, and 1%, respectively.

3. Conclusions

This study aimed to test whether economic volatility exerts differentiated effects on indicators and losses pertaining to road traffic accidents. To that end, we examined China's road traffic accidents spanning from 1999 to 2018 and discussed the different effects of five commonly used economic indicators, namely, average salaries, employment, unemployment, total mileage of highway, and private vehicle ownership, on the number of road traffic accidents, injuries, fatalities, and direct economic losses, followed by an investigation of the long-term equilibrium and short-term interactions among these indicators using the ARDL-ECM model. We found that all economic indicators except average salaries have a long-term equilibrium with road traffic accident indicators, and their long-term relationships are more salient than their counterparts over the short term. Specifically, employment is negatively correlated with road traffic accidents and that of fatalities, but positively correlated with injuries and direct economic losses. For every 1% increase in employment, the road traffic accidents and fatalities decrease by 0.085% and 0.145%, respectively, whereas injuries and direct economic losses increase by 0.12% and 0.031%, respectively. The opposite stands true for the relationship between unemployment and these road traffic accident indicators; for every 1% increase in unemployment, road traffic accidents increase by 0.395%, but injuries and direct economic losses decrease by 0.549% and 0.125%, respectively. The total mileage of highway and road traffic accidents are negatively correlated with injuries, but positively correlated with fatalities and direct economic losses. For every 1% increase in the total mileage of highway, road traffic accidents and injuries decrease by 1.121% and 1.822%, respectively, whereas fatalities and direct economic losses increase by 3.386% and 0.431%, respectively. Private vehicle ownership is positively correlated with fatalities; for every 1% increase in private vehicle ownership, fatalities increase by 0.146%. The Granger causality test showed that, over the short term, an increase in employment could lead to an increase in injuries, an increase in private vehicle ownership results in a rise in fatalities, and the short-term variations in road traffic accidents, injuries, and fatalities directly affect changes in the total mileage of highway.

We found that volatility in economic indicators exerts significantly different effects on road traffic accidents, injuries, and fatalities. Such a finding may help us to establish preventative measures that are more economically efficient.

3.1. Employment and Road Traffic Safety

Our study finds that poor employment prospects lead to an increase in road traffic accidents and fatalities, while improvements in employment further lead to an increase in injuries and direct economic losses. We recommend that greater legislative efforts should be pursued in times of economic recessions to regulate drunk driving and over-speeding, reduce upper speed limits of highways, and standardize the use of safety belts in order to avoid the occurrence of fatal accidents. When the employment rate increases, more efforts should be put into providing publicity and guidance related to public safety, especially during peak commuting hours and at places like crossroads that involve high pedestrian and vehicle flows [30]. A good cultural atmosphere revolving around traffic safety should also be created in order to raise people's safety awareness and prevent the occurrence of injury accidents [31].

3.2. Total Mileage of Highway and Road Traffic Safety

Over the short term, the frequent occurrences of road traffic accidents will inhibit the increase in the total mileage of highway. A failure to effectively control the occurrences of these accidents may affect the overall decision-making taking place in local governments and relevant management authorities over the short term, thereby producing a negative impact on the development of regional road traffic. To address the issue, we recommend that protection fences be erected for different types of road sections to raise the level of road traffic safety, on the one hand [32], and warning signs should also be put up around areas entailing frequent occurrences of accidents, on the other hand. Improvements in road traffic can only be achieved by ensuring the conscientious development of road traffic safety.

3.3. Private Vehicle Ownership and Road Traffic Safety

Over the long term, private vehicle ownership is positively correlated with road traffic accidents, and a short-term increase in private vehicle ownership inevitably leads to a rise in fatalities. To avoid the rise in fatalities caused by increased private vehicle ownership, approaches like increasing the difficulty in obtaining drivers' licenses or setting up classified drivers' licenses can be implemented in order to increase drivers' proficiency and avoid high accident rates caused by novice drivers [33]. Additionally, studies have shown that risky driving behaviors such as the frequent use of mobile phones also increase the fatality rate of non-professional drivers [34]. Thus, such behaviors can be reduced through the implementation of an electronic policing system or the provision of adequate publicity and guidelines.

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