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Abstract

We applied Smeed's Law to Japanese prefectural data from between 1988 and 2016. We found that the coefficient for the number of vehicles was stable over the estimation period, but that the constant term decreased gradually. We decomposed fatalities per capita into fatalities per accidents and accidents per capita, and applied regression equations to the data. We conclude the following from this study. First, the relationship between fatalities per capita and the number of registered vehicles per capita was stable, which is consistent with Smeed's Law. Second, the effects of technological advances have changed the estimated coefficients for time dummies. The role of hospitals may be difficult to incorporate into Smeed's Law because of the complicated relationship between the distance to hospital and fatalities per capita.

JEL Classification Number: R41, I18, R42
Keywords: Smeed's Law, Traffic Accidents, Fatalities, Hospitals

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Smeed's Law and the Role of Hospitals in Modeling Fatalities and Traffic Accidents

1. INTRODUCTION

After Smeed (1949) found a relationship between the numbers of fatalities and vehicles, researchers have continued to apply this law in many countries.[2] For example, Tamura (2013) has studied this law in Japan. However, this recent research by Tamura (2013) has indicated that the law is not stable over time in Japan.

One question about the stability of Smeed's Law is that it does not incorporate safety improvements in automobiles involved in traffic accidents or advances in medical technologies. For example, one of the earliest studies, by Pantridge and Geddes (1967), involved the cardiology unit and found that the time to hospital was one of the most important factors affecting patient survival. Jones and Bentham (1995) also investigated the effect of time to hospital. Technological advances in automobile safety and emergency rescue at traffic accidents can also affect survival. For example, since the law requiring installation of airbags and provision of quicker transportation to hospitals, the survival of seriously injured people has increased.

This paper investigated the possible need for structural changes in Smeed's Law and the role of hospitals in Japan. We reformulated Smeed's Law and used panel data in Japan to estimate whether the distance to hospital is an explanatory variable. We then decomposed the fatalities per capita into the number of fatalities per accidents and traffic

[2] There are several models to explain the number of fatalities in traffic accidents that do not refer to Smeed's Law. For example, Grimm and Treibich (2013) investigated the determinants of fatalities in different kinds of traffic accidents and found that income could explain the differences.

accidents per capita. We also explain the determinants of these two variables using Japanese prefectural data between 1988 and 2016.

In section 2 of this paper, we first reformulate and decompose Smeed's Law and extend it by using a model that includes the distance to hospital. In section 3, we decompose the fatalities per capita into two parts and estimate the relationships between related variables. Finally, we conclude by discussing the empirical implications of the relationships between a stable Smeed's Law and the role of hospitals.

2. SMEED'S LAW AND THE ROLE OF HOSPITALS

2.1 Traditional Approach to Smeed's Law

Smeed's original law is described as follows:

$$\mathrm{Ndeath} = 0.00030 * (\mathrm{Nveh} * \mathrm{Pop}^2)^{\frac{1}{3}}.$$

where Ndeath is the number of fatalities in traffic accidents, Nveh is the number of registered vehicles, and Pop is the size of the population, usually 100,000. This relationship can be rewritten as number of fatalities per registered number of vehicles:

$$\frac{\mathrm{Ndeath}}{\mathrm{Nveh}} = 0.00030 * \left(\frac{\mathrm{Nveh}}{\mathrm{Pop}}\right)^{-\frac{2}{3}}$$

or fatalities per capita:

$$\frac{\mathrm{Ndeath}}{\mathrm{Pop}} = 0.00030 * \left(\frac{\mathrm{Nveh}}{\mathrm{Pop}}\right)^{\frac{1}{3}}.$$

We linearized this using logarithmic transformation and generalized to estimate data from other countries as follows:

$$\ln\left(\frac{\text{Ndeath}}{\text{Nveh}}\right) = \alpha_0 - \alpha_1 \ln\left(\frac{\text{Nveh}}{\text{Pop}}\right), \tag{1}$$

or

$$\ln\left(\frac{\text{Ndeath}}{\text{Pop}}\right) = \beta_0 + \beta_1 \ln\left(\frac{\text{Nveh}}{\text{Pop}}\right).[3] \tag{2}$$

Using Japanese prefectural data between 1988 and 2016, we applied the above equation (2). In practice, we added prefectural and time dummies to control the individual and time effects. Additionally, to capture the possibility that time could alter the coefficient for $\ln\left(\frac{\text{Nveh}}{\text{Pop}}\right)$, we adopted the products of the trend term (Time) and $\ln\left(\frac{\text{Nveh}}{\text{Pop}}\right)$ as explanatory variables.

Before we explain the estimation results, we first describe the data source (Table I) and variables that we used in this paper and their summary statistics (Table II). The estimated results of several specifications are shown in Table III. From the viewpoint of the maximum adjusted R-squared or minimum Akaike's information criterion (AIC), Model 1C is the best model. This model is a simple least-square with dummy variables (LSDV) model.[4] The estimated coefficient of β_1 was 0.962085, which means that α_1 in equation (1) is 0.037013. We could not reject the hypothesis $\alpha_1 = 0$.[5] However, the

[3] Hesse et al. (2016) and Koren and Borsos (2010) also investigate Smeed's Law in the form of the same dependent variable (fatalities per capita).
[4] Ponnaluri (2012) took a similar approach to Indian panel data and found regional differences between states.
[5] The estimated standard error for the coefficient was 0.0883.

estimated results indicated significant and stable relationships between the number of fatalities in traffic accidents and registered vehicles.[6]

To investigate the effects of technological advances, we estimated the coefficients for time dummies in Model 1C in Figure 1. This figure implies that the probability of death in traffic accidents gradually decreases during this period as the relationship between number of deaths and vehicles remains stable. We consider that these changes reflect the technological advances applied to the rescue of victims in traffic accidents. This result is consistent with Oppe's (1991) findings for Japanese data.

2.2 Accessibility to Hospitals

When considering technological advances or transportation time to hospitals, one should add some explanatory variables to equation (2). In this paper, we modified the constant term as a linear function of the distance to hospital:

$$\beta_0 = \theta_0 + \theta_2 \ln(\mathrm{Hdist})$$

where Hdist is the distance to hospital. In this paper, we estimated the distance to hospital using the following steps:

1. We estimated each hospital's area of coverage.
2. We assumed that each area is circular.
3. Using the formula to estimate the area of the circle, we estimated the radius of the circle.

Using these steps, we estimated Hdist as:

[6] Smith (1999) found a negative correlation between number of fatalities and vehicles using OECD cross-sectional data. Our result is different from that of Smith (2010), but our specification is expressed per capita.

$$\mathrm{Hdist} = \sqrt{\frac{\mathrm{Area}}{\mathrm{Nhospital}} \Big/ \pi}$$

where $\mathrm{Nhospital}$ is the number of hospitals in each prefecture, Area is the total area of each prefecture, and π is the circular constant. We then modified equation (2) to:

$$\ln\left(\frac{\mathrm{Death}}{\mathrm{Pop}}\right) = \theta_0 + \theta_1 \ln\left(\frac{\mathrm{Nveh}}{\mathrm{Pop}}\right) + \theta_2 \ln(\mathrm{Hdist}). \qquad (3)$$

In this empirical estimation, we estimated equation (3) in a similar way as for equation (2). The estimation results are reported in Table IV. Model 2B produced the minimum AIC. The estimated coefficient for $\ln\left(\frac{\mathrm{Nveh}}{\mathrm{Pop}}\right)$ was 1.12921, which means that α_1 in equation (1) was –0.12921. We also could not reject the hypothesis $\alpha_1 = 0$.[7] The estimated coefficient for the additional variable $\mathrm{Time} * \ln(\mathrm{Hdist})$ was negative and was statistically significant. This result implies that the number of fatalities in traffic accidents per capita decreases when the distance to hospital increases. This is not a plausible result. In the following sections, we try to explain this result.

3. DECOMPOSITION APPROACH

To investigate why the distance and fatalities per capita correlated negatively correlated, as shown in section 2.2, we decomposed the dependent variable in equation (3) as:

$$\frac{\mathrm{Ndeath}}{\mathrm{Pop}} = \frac{\mathrm{Ndeath}}{\mathrm{Accident}} * \frac{\mathrm{Accident}}{\mathrm{Pop}}.$$

To investigate this reason, we applied the following two equations:

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[7] The estimated standard error for the coefficient was 0.1210.

$$\ln\left(\frac{\text{Ndeath}}{\text{Accident}}\right) = \gamma_0 + \gamma_1 \ln\left(\frac{\text{Nveh}}{\text{Pop}}\right) + \gamma_2 \ln(\text{Hdist}), \tag{4}$$

and

$$\ln\left(\frac{\text{Accident}}{\text{Pop}}\right) = \delta_0 + \delta_1 \ln\left(\frac{\text{Nveh}}{\text{Pop}}\right) + \delta_2 \ln(\text{Hdist}). \tag{5}$$

The estimated results for equation (4) are shown in Table V. Model 3C produced the minimum AIC. This result shows that the number of fatalities per accident correlated positively with the products of the trend term and the distance to hospital: $\text{Time} * \ln(\text{Hdist})$ This variable is also included in Table IV, which shows the estimation results of equation (3). This result seems to be natural. If the distance to hospital increases, the access time to hospital for an injured person in a traffic accident also increases, and the potential of a fatality becomes high.

The estimated results for equation (5) are shown in Table VI. Model 4B produced the minimum AIC. This result shows that the number of accidents per capita correlated negatively with the products of the trend term and the distance to hospital: $\text{Time} * \ln(\text{Hdist})$ This variable is also included in Table IV, which shows the estimation results of equation (3). This relationship explains the implication that the number of fatalities in traffic accidents per capita decreases when the distance to hospital increases when estimated using equation (3). However, we could not identify any reason why the number of accidents per capita increased when the number of hospitals increased and the distance to hospital decreased.

Next, we investigated the possibility that there is reverse causality between the two variables.[8] We estimated the following regression equation:

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[8] Some researchers have investigated the number of traffic accidents. For example, Hakim et al. (1991) reviewed models for traffic accidents and proposed some additional variables as explanatory variable in macro models. In this paper, we did not search for the best model to explain the number of traffic accidents. For example, Bishai et al. (2006)

$$\ln(\text{Hdist}) = \phi_0 + \phi_1 \ln\left(\frac{\text{Nveh}}{\text{Pop}}\right) + \phi_2 \ln\left(\frac{\text{Accident}}{\text{Pop}}\right). \quad (6)$$

In practice, to capture the possibility that the time coefficient varied for $\ln\left(\frac{\text{Nveh}}{\text{Pop}}\right)$ and $\ln\left(\frac{\text{Accident}}{\text{Pop}}\right)$, we adopted the products of the trend term (Time) and both $\ln\left(\frac{\text{Nveh}}{\text{Pop}}\right)$ and $\ln\left(\frac{\text{Accident}}{\text{Pop}}\right)$ as explanatory variables. Additionally, we approximated the nonlinear relationship between $\ln(\text{Hdist})$ and $\ln\left(\frac{\text{Accident}}{\text{Pop}}\right)$, and we added $\left(\ln\left(\frac{\text{Accident}}{\text{Pop}}\right)\right)^2$ as an additional explanatory variable. The estimation results with several specifications are shown in Table VII. Model 5C produced the minimum AIC model. In this result, the relationship between $\ln(\text{Hdist})$ and $\ln\left(\frac{\text{Accident}}{\text{Pop}}\right)$ was unclear because the estimated relationship was quadratic. According to Table II, we estimated the relationship between Hdist and $\frac{\text{Accident}}{\text{Pop}}$ when $\frac{\text{Accident}}{\text{Pop}}$ was from 1.822 (=exp(0.6)) to 13.4637 (=exp(2.6)), which were the minimum and maximum values, respectively. Figure 3 shows that the estimated relationship between these two variables was negative.

We considered that hospitals were constructed in areas where traffic accidents occurred frequently during these years. In other words, people made the distance to hospitals shorter in the place where traffic accidents occurred frequently. This is a natural policy to cope with injured people in traffic accidents.

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investigated the determinants of the number of traffic accidents and found that GDP, population, number of vehicles, and length of roads were significant factors. However, their results are not useful for investigating traffic accidents per capita in prefectures in Japan because the time series data are relatively short and road lengths are almost fixed during the sample period. García-Ferrer, De Juan, and Poncela (2007) also investigated the relationship between number of traffic accidents and economic activity by constructing time series models with monthly data. We could not obtain monthly data, and therefore, we could not construct such a complicated model to investigate the number of traffic accidents. These are questions for future investigations of the determinants of traffic accidents per capita.

Following the estimation result described above, we next estimated equation (2) by adding $\left(\ln\left(\frac{\text{Accident}}{\text{Pop}}\right)\right)^2$ as an additional explanatory variable. We obtained the following result:

$$\ln\left(\frac{\text{Death}}{\text{Pop}}\right)$$

$$= 1.050 * \ln\left(\frac{\text{Nveh}}{\text{Pop}}\right) - 0.00178 * \left(\text{Time} * \ln(\text{Hdist})\right) + 0.0144 * \left(\ln\left(\frac{\text{Accident}}{\text{Pop}}\right)\right)^2 + (\text{others})$$

$$(8.286) \qquad\qquad (-1.375) \qquad\qquad\qquad (2.075).$$

where *t* values are in parentheses. In this result, the estimated coefficient for $\ln(\text{Hdist})$ remained negative, but it was not statistically significant. We conclude that this reflects a reverse causality between the two variables.

4. CONCLUSION

In this paper, we estimated Smeed's Law using Japanese prefectural data from between 1988 and 2016 in the form of $\ln\left(\frac{\text{Ndeath}}{\text{Pop}}\right) = \beta_0 + \beta_1 \ln\left(\frac{\text{Nveh}}{\text{Pop}}\right)$. We then confirmed that the coefficient of $\ln\left(\frac{\text{Nveh}}{\text{Pop}}\right)$ was stable over the estimation period, but the constant term decreased gradually. The latter phenomenon might be related to the technological advances in the rescue of victims of traffic accidents. Including the distance to hospital as an additional explanatory variable to explain the role of hospital in Smeed's

Law did not produce plausible results because of the complicated relationships between $\ln\left(\frac{\text{Death}}{\text{Pop}}\right)$ and $\ln(\text{Hdist})$. We decomposed the number of fatalities per capita into $\ln\left(\frac{\text{Ndeath}}{\text{Accident}}\right)$ and $\ln\left(\frac{\text{Accident}}{\text{Pop}}\right)$, and we used different regression equations with the same explanatory variables. Finally, we reached the following conclusions. First, the relationship between fatalities per capita and number of registered vehicles per capita is stable, which is also implied by Smeed's Law. However, estimation using the traditional linearized form:

$$\ln\left(\frac{\text{Ndeath}}{\text{Nveh}}\right) = \alpha_0 - \alpha_1 \ln\left(\frac{\text{Nveh}}{\text{Pop}}\right),$$

which is used by most researchers, could not produce statistically significant relationships. Second, the effect of technological advances is reflected in changes in the estimated coefficients for time dummies. However, the role of hospitals is difficult to incorporate into Smeed's Law because of the complicated relationship between the distance to hospital and fatalities per capita.

Finally, we note some remaining problems. We found it difficult to model the role of hospitals when modeling traffic accidents, but we have not proposed any solutions. Our analysis was limited to Japanese data, and it may not be applicable to use our decomposition approach in other countries to check the robustness of our findings. These are remaining problems for future research.

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Table I. Sources of Data

Variable	Data	Survey Date	Year	Source
Accidents	Number of Traffic Accidents	Calendar Year	1988–2015	National Police Agency
Ndeath	Number of Fatalities in Traffic Accidents	Calendar Year	1988–2015	National Police Agency
Nveh	Number of Registered Vehicles	End of March	1988–2015	Car ownership number: Automobile Inspection & Registration Information Association
Pop	Prefecture Population	October 1	1987–2014	Basic resident register
Nhospital	Number of Hospitals	October 1	1988–2015	Medical Facilities Survey: Ministry of Health, Labor and Welfare
Area	Prefecture Area	October 1	1985, 1990, 1995, 2000, 2005, 2010, 2015	Census: Statistical Survey Department, Statistics Bureau, Ministry of Internal Affairs and Communications

Note: We fixed the area data in 1985–1989 to be equal to the surveyed data in 1985 and the data after 1990 are fixed in the same manner.

Table II. Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
$\ln\left(\frac{\text{Ndeath}}{\text{Pop}}\right)$	–2.69361	0.45435	–4.43015	–1.73229
$\ln\left(\frac{\text{Ndeath}}{\text{Accident}}\right)$	–4.43517	0.50995	–5.70787	–3.31624
$\ln\left(\frac{\text{Accident}}{\text{Pop}}\right)$	1.74157	0.32360	0.60851	2.58690
$\ln\left(\frac{\text{Nveh}}{\text{Pop}}\right)$	6.43783	0.20993	5.78853	6.80430
$\ln(\text{Hdist})$	1.22407	0.45435	–4.43015	–1.73229

Table III. Estimation Results of Traditional Models

Dependent Variables	$\ln\left(\frac{\text{Ndeath}}{\text{Pop}}\right)$				
	Model 1A	Model 1B	Model 1C	Model 1D	Model 1E
$\ln\left(\frac{\text{Nveh}}{\text{pop}}\right)$	0.098858	–1.94222	0.962085	0.959081	1.53061
	(1.657)	(–37.624)	(10.894)	(6.093)	(25.371)
$\text{Time} * \ln\left(\frac{\text{Nveh}}{\text{pop}}\right)$	—	—	—	0.00007541	–0.0095714
				(0.023)	(–63.4000)
Time Dummies	No	No	Yes	Yes	No
Prefectural Dummies	No	Yes	Yes	Yes	Yes
Constant	Yes	No	No	No	No
Adjusted R-squared	0.0013	0.6957	0.9344	0.9343	0.9270
AIC	829.277	69.7879	–926.534	–925.534	–869.179

Note: *t* values are in parentheses.

Table IV Estimation Results of Accessibility to Hospital Models

Dependent Variable	$\ln\left(\frac{Ndeath}{Pop}\right)$		
	Model 2A	Model 2B	Model 2C
$\ln\left(\frac{Nveh}{pop}\right)$	1.00248	1.03195	1.12921
	(6.109)	(6.427)	(9.332)
$Time * \ln\left(\frac{Nveh}{pop}\right)$	0.00363244	0.00329325	—
	(1.011)	(0.922)	
$\ln(Hdist)$	–0.106817	—	—
	(–0.872)		
$Time * \ln(Hdist)$	–0.00287974	–0.00302830	–0.00251735
	(–2.093)	(–2.218)	(–2.002)
Time Dummies	Yes	Yes	Yes
Prefectural Dummies	Yes	Yes	Yes
Constant	No	No	No
Adjusted R-squared	0.9345	0.9345	0.9345
AIC	–926.546	–927.142	–927.690

Note: *t* values are in parentheses.

Table V. Estimation Results of Fatalities per Accidents Models

Dependent Variable	$\ln\left(\frac{\text{Ndeath}}{\text{Accident}}\right)$		
	Model 3A	Model 3B	Model 3C
$\ln\left(\frac{\text{Nveh}}{\text{pop}}\right)$	0.209680	—	—
	(0.854)		
$\text{Time} * \ln\left(\frac{\text{Nveh}}{\text{pop}}\right)$	–0.032053	–0.029014	–0.028817
	(–5.959)	(–7.195)	(–7.150)
$\ln(\text{Hdist})$	–0.196897	–0.229130	—
	(–1.074)	(–1.278)	
$\text{Time} * \ln(\text{Hdist})$	0.020719	0.021113	0.020905
	(10.062)	(10.523)	(10.451)
Time Dummies	Yes	Yes	Yes
Prefectural Dummies	Yes	Yes	Yes
Constant	No	No	No
Adjusted R-squared	0.8836	0.8836	0.8835
AIC	–396.123	–396.736	–396.869

Note: *t* values are in parentheses.

Table VI. Estimation Results of Per Capita Accidents Models

Dependent Variables	$\ln\left(\frac{\text{Accident}}{\text{Pop}}\right)$	
	Model 4A	Model 4B
$\ln\left(\frac{\text{Nveh}}{\text{pop}}\right)$	0.792801	0.0767950
	(4.133)	(4.092)
$\text{Time} * \ln\left(\frac{\text{Nveh}}{\text{pop}}\right)$	0.035686	0.035972
	(8.493)	(8.613)
$\ln(\text{Hdist})$	0.090081	—
	(0.629)	
$\text{Time} * \ln(\text{Hdist})$	–0.023599	–0.023474
	(–14.671)	(–14.710)
Time Dummies	Yes	Yes
Prefectural Dummies	Yes	Yes
Constant	No	No
Adjusted R-squared	0.8235	0.8236
AIC	–721.073	–721.862

Note: *t* values are in parentheses.

Table VII Estimation Results of Checking Reverse Causality

Dependent Variable	ln(Hdist)		
	Model 5A	Model 5B	Model 5C
$\ln\left(\frac{Nveh}{pop}\right)$	–0.107059	–0.223446	–0.220667
	(–0.238)	(–5.698)	(–6.054)
$Time * \ln\left(\frac{Nveh}{pop}\right)$	0.0046643	0.00422610	0.00417486
	(3.640)	(5.238)	(5.483)
$\left(\ln\left(\frac{Nveh}{pop}\right)\right)^2$	–0.00977686	—	—
	(–0.260)		
$\ln\left(\frac{Accident}{Pop}\right)$	–0.119793	–0.119768	–0.121706
	(–5.159)	(–5.238)	(–5.819)
$Time * \ln\left(\frac{Accident}{Pop}\right)$	–0.0000904455	–0.0000710097	—
	(–0.241)	(–0.193)	
$\left(\ln\left(\frac{Accident}{Pop}\right)\right)^2$	0.035709	0.035602	0.035762
	(5.646)	(5.643)	(5.720)
Time Dummies	Yes	Yes	Yes
Prefectural Dummies	Yes	Yes	Yes
Constant	No	No	No
Adjusted R-squared	0.9962	0.9962	0.9962
AIC	–2854.769	–2855.733	–2856.713

Note: *t* values are in parentheses.

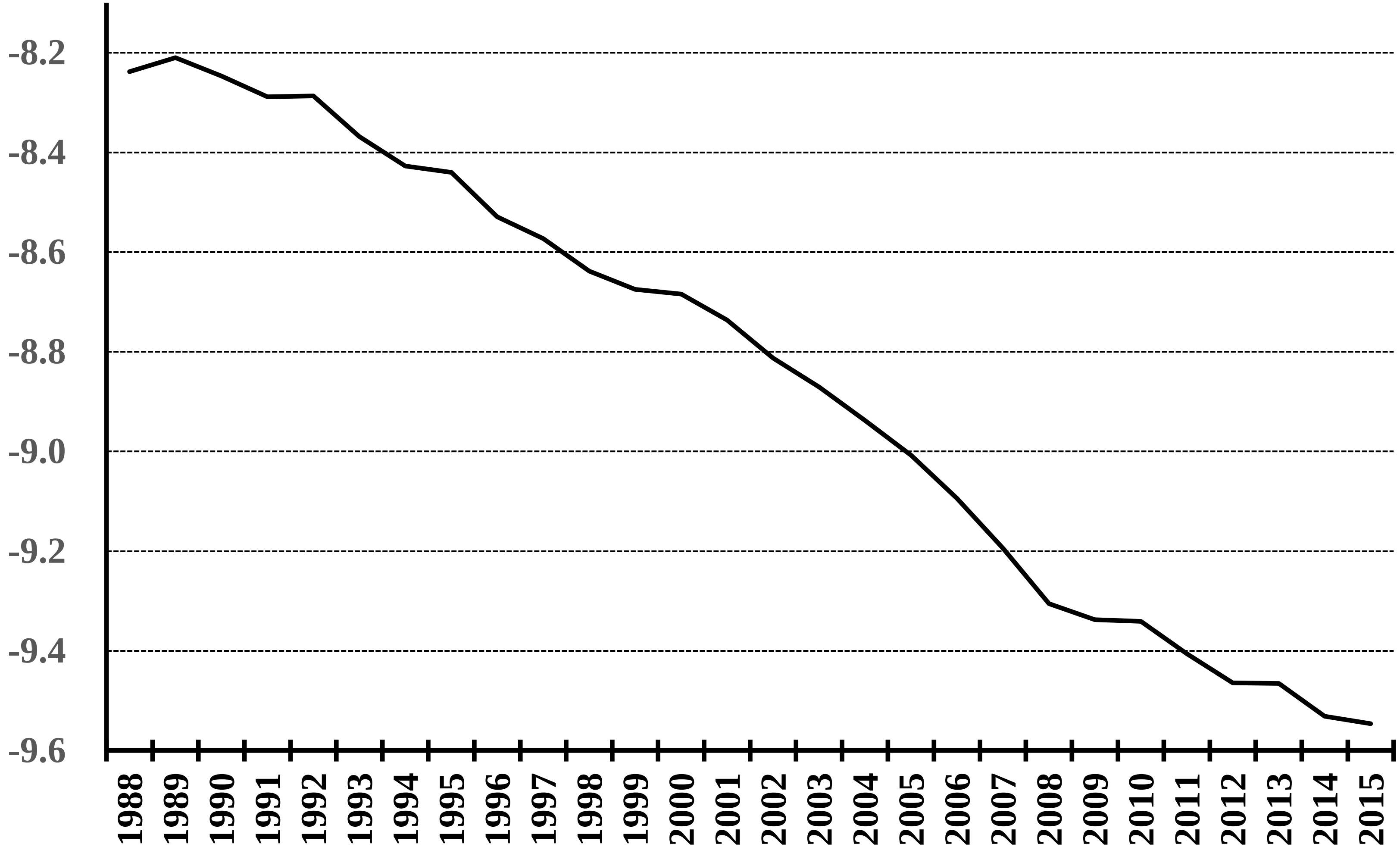

Figure 1 Estimated Coefficients of Time Dummies in Model 1C

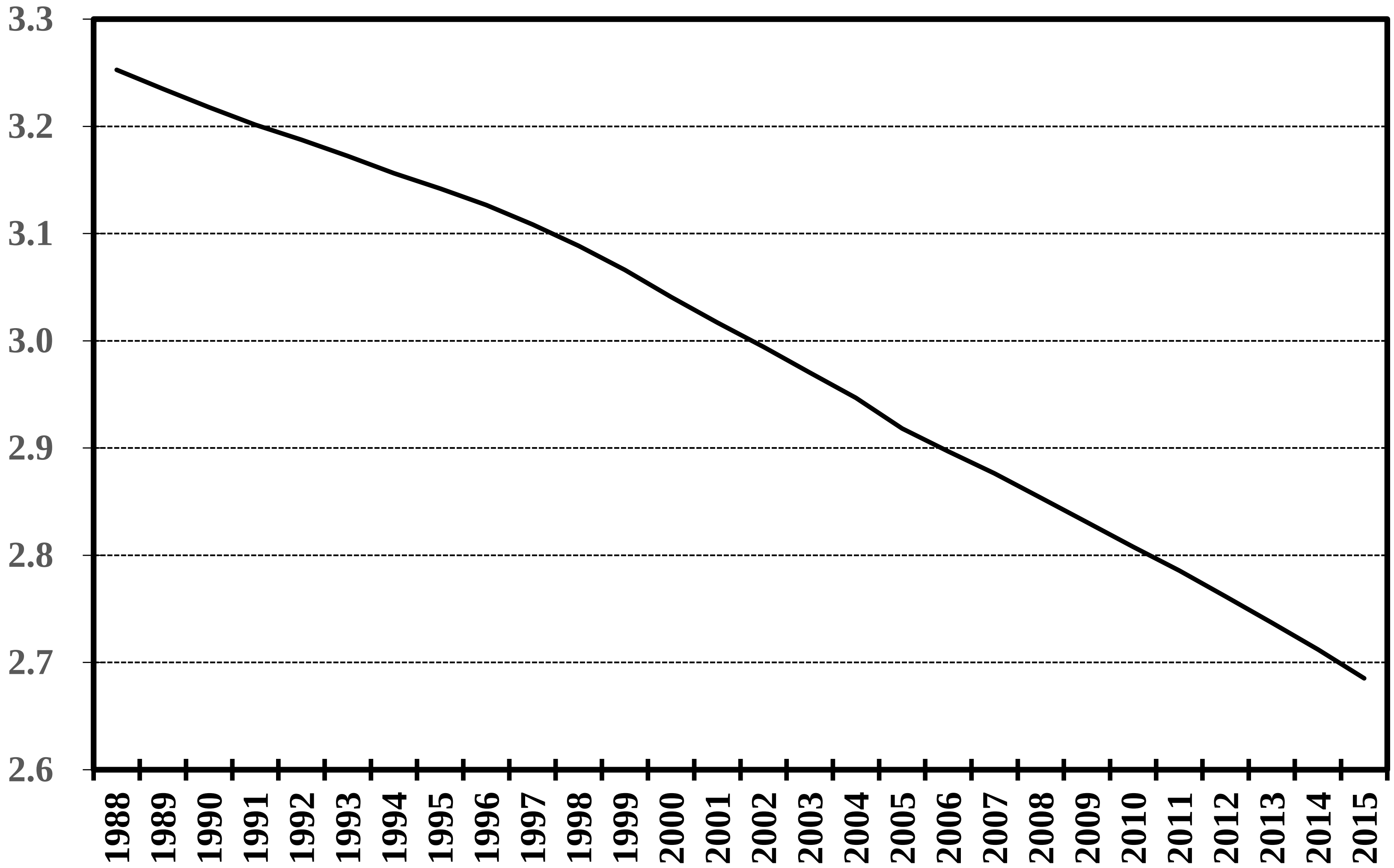

Figure 2 Estimated Coefficients of Time Dummies in Model 5C

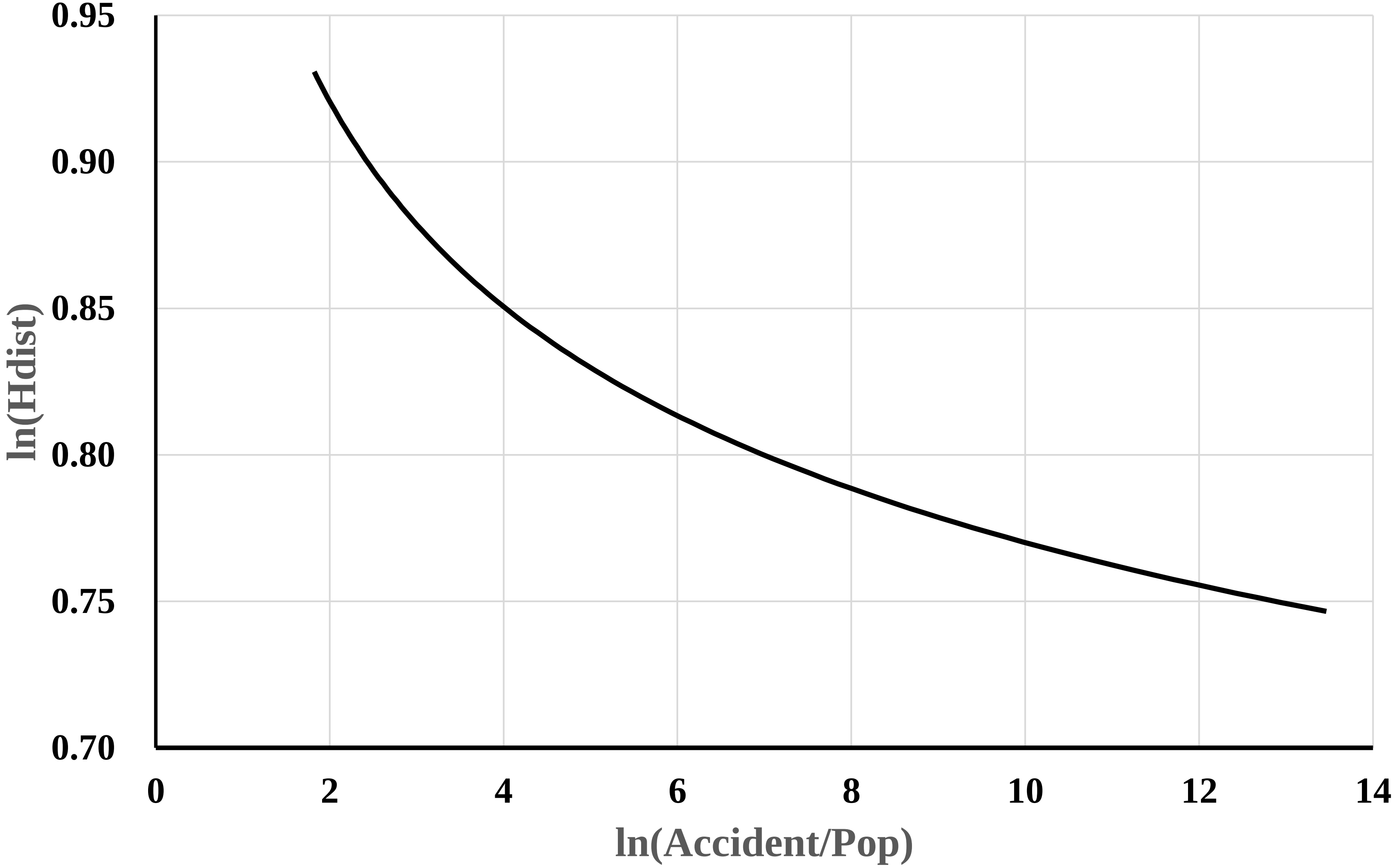

Figure 3 Relationship between Distance to Hospital and Accidents Per Capita