Size of economic activity and occurrence of fatal traffic accidents: a count panel data analysis on Fukuoka prefecture in Japan[*]

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Abstract:
In this paper, the investigation is conducted on the relationship between the number of fatalities by dint of traffic accidents and the gross municipal product, by using the panel data whose cross-sectional units are composed of municipalities in Fukuoka Prefecture in Japan. It turns out that the conventional quasi-differenced GMM estimator gives unconvincing results, while some of the GMM estimators proposed by Kitazawa (2007) give convincing results. The convincing results suggest that the diseconomy of scale is recognized in the occurrence of traffic fatalities.

Keywords: traffic accident, number of fatalities, gross municipal product, count panel data, GMM, diseconomy of scale
JEL classification: C23, I12, R41

1. Introduction

The investigation of the relationship between traffic accidents and economic activity is conducted in many literatures. Joksch (1984) finds the positive relationship between the change of motor vehicle deaths and the change of industrial production index in the U.S. time series data, while Wagenaar (1984) reveals the concurrent negative relationship between the unemployment rate and the number of drivers involved in the crash accidents and the lag one positive relationship between these variables in the data of Michigan in the U.S. In addition, Garcìa-Ferrer et al. (2007) show that economic activity and traffic accidents have a common cyclical behavior using Spanish time series data, while Scuffham (2003) obtains the result that increase in either real gross domestic per capita or unemployment rate is related with decreases in fatal crashes using New Zealand's time series data. In cross-section analysis, using the data on counties in Ohio state in the U.S., Traynor (2008) investigates the relationship between crash fatality rates and per capita income allowing for the usage of highways and Traynor (2009) obtains the result that the economic prosperity protects individuals involved in traffic accidents from serious injury or fatality, while using the data of 30 member and five accession countries of OECD and the correlation analysis, Gaygisiz (2009) shows the negative association of GDP per capita with road-traffic accident fatality rate and the positive association of Gini index and unemployment rate with the fatality rate as well as the association of cultural characteristics etc. with the fatality rate. In panel data analysis, the positive relationships between economic amelioration and motor vehicle deaths are found by Ruhm (2000) using data for states and District of Colombia in the U.S., by Neumayer (2004) using data for German states, and by Gerdtham and Ruhm (2006) using data for OECD countries, respectively, while Bishai et al. (2006) estimate the negative and almost zero elasticities of GDP to fatalities when the multivariate ordinary least square (OLS), fixed effects (FE), and random effects (RE) regressions are applied for higher income countries and all countries in their panel data. Further, inverted U-shaped relationships are found by Van Beeck et al. (2000), Koptis and Cropper (2005), and Bishai et al. (2006) in scatter plots on relationships between road deaths divided by population and the

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prosperity level (e.g. GDP per capita), by Paulozzi et al. (2007) in some relationships between motor vehicle crash mortality rates and economic development, by Moniruzzaman and Andersson (2008) in time series plot of mortality rates due to road traffic accidents as well as in the scatter plot, and by Law et al. (2009) in count panel regression of motorcycle deaths on per capita income, respectively.[1] In Japan, Suhama (2003) obtains the results suggesting the positive association between traffic accidents and economic activity, by using demographic and economic data in Chugoku region in Japan and Poisson regression.

As a part of the investigation of the relationship between traffic accidents and economic activity, this paper investigates the elasticity of traffic fatalities to gross municipal product (GMP), by using panel data of 96 municipalities in Fukuoka prefecture in Japan over the spans within the period 1990-2003. In this case, the GMP (which is the explanatory variable) is a continuous variable, while the number of traffic fatalities (which is the dependent variable) is a count variable (whose values is often zero). This investigation uses the estimators newly proposed by Kitazawa (2007) for the linear feedback model proposed by Blundell et al. (2002). The newly proposed GMM estimators (i.e. the GMM(pr), GMM(sa), and GMM(sb) estimators) are not only consistent under the assumptions of the predetermined explanatory variable, but also expected to behave well in small sample, compared to the conventional GMM estimator (i.e. the GMM(qd) estimator proposed by Chamberlain (1992) and Wooldridge (1997)), as suggested by Monte Carlo experiments in Blundell et al. (2002) and Kitazawa (2007).[2] The elasticity is explored in short spans, comparing the estimation results using these newly proposed GMM estimators with those using the conventional GMM estimator and other estimators. To the best of my knowledge, this paper is the first approach which investigates the GMP elasticity of traffic fatalities by applying the estimation technologies brand-new at the present stage to the cross-municipality panel data.

Panel data analysis using short-run time period has an advantage over time series analysis, concerning the fact that it can investigate the relationship between size of economic activity and traffic fatalities without taking into consideration the possibility that in more recent years, the advances of the emergency medical service (EMS) and the fail-safe (FS) of vehicles decrease the traffic fatalities, which seems to materialize along with the temporal development of the economic activity. Time series analysis using long-run time period has a possibility to generate the result suggesting the relationship between the advances of EMS and FS and the traffic fatalities. In addition, the individual specific effects in panel data model can control for the differences of EMS and FS among the municipalities.

The rest of the paper is organized as follows. In section 2, the LFM is presented and the estimators are introduced. In section 3, the explanation on the dataset is conducted. In section 4, the estimation results are presented. Section 5 concludes.

2. Model and Estimators

In this section, the following linear feedback model (LFM) in count panel data (CPD) is assumed between the number of fatalities y_{it} and the natural logarithm of the gross municipal product (GMP) x_{it} for municipality i at year t :

$$y_{it}=\gamma y_{i,t-1}+\exp(c+\beta x_{it}+\eta_i)+v_{it} \quad , \qquad \text{for} \quad t=2,\ldots,T \quad , \tag{1}$$

where γ and β are parameters of interest to be estimated, c is the constant, η_i is the

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[1] Anbarti et al. (2009) investigate the influence of income equality on traffic fatality rate, as well as the inverted U-shape.

[2] The primordial form of the additional moment conditions used in the GMM(pr) estimator is that developed by Windmeijer (2000).

fixed effect specific to municipality i, and v_{it} is the disturbance.[3] The assumption on the disturbance here is

$$E[v_{it}|y_{i1}, v_i^{t-1}, x_i^t, \eta_i]=0 \quad , \qquad \text{for} \quad t=2,\ldots,T \quad , \tag{2}$$

by taking into consideration the serially uncorrelated disturbance and the predetermined explanatory variable x_{it}, where $v_i^{t-1}=(v_{i1},\ldots,v_{i,t-1})$. It is adequate to regard GMP as the predetermined variable rather than the strictly exogenous variable, since it is conceivable that the current fatalities have an influence on the future GMP.

Equation (1) is estimated by the estimators presented in Kitazawa (2007). Under the assumption (2) and when T is fixed and $N \rightarrow \infty$, the GMM(qd) and GMM(pr) estimators are consistent, the GMM(sa) and GMM(sb) estimators are consistent if y_{it} and x_{it} are stationary, and the PSM (pre-sample mean) estimator proposed by Blundell et al. (1999) and Blundell et al. (2002) is consistent if the pre-sample length of the dependent variables to be used is large, the fixed effect composing the explanatory variable is proportional to the fixed effect in the regression for each municipality, and the (finite) moment generating functions of the disturbance terms composing the explanatory variables are equal over time and for all municipalities. On the contrary, the Level estimator ignoring the fixed effects, WG (within group) estimator proposed by Blundell et al. (2002), and GMM(ex) estimator proposed by Kitazawa (2007) are inconsistent in such a situation.[4] However, it is presumable that the usage of the GMM(qd) estimator is conducive to the serious downward bias in small sample. It is shown in the Monte Carlo experiments by Blundell et al. (2002) and Kitazawa (2007) that GMM(qd) estimator does not performs well in small sample.

3. Dataset

The numbers of traffic fatalities in municipalities (which are composed of cities, towns, and villages) in Fukuoka prefecture are collected from the Traffic Almanacs issued by the Headquarter of Fukuoka Prefectural Police, while the gross municipality products (GMP) in municipalities are collected from the Report on Prefectural and Municipal Accounts issued by the Research and Statistics Division of Fukuoka Prefecture.[5] These data were displayed on the website, Fukuoka Data Web, set up by the Statistical Association of Fukuoka Prefecture.[6] The GMP (in million Japanese yen) is deflated by using the general consumer price index (excluding imputed rent) with base year being 2005 issued by the Statistics Bureau, Ministry of Internal Affairs and Communications.

The 96 municipalities are collected, allowing for the synoecism. The time periods in the dataset are 1990-2003 for the GMP and 1969-2003 for the number of fatalities, respectively. Accordingly, the estimations are conducted for the spans in the period 1990-2003 and therefore the data of the fatalities before 1990 is entirely dedicated to the calculation of the pre-sample mean.

The first-order serial correlation coefficients for the numbers of fatalities are calculated in the period 1969-2003 for all municipalities. The histogram of the correlation coefficients is depicted in Figure 1a. The summit of frequencies is recognized in the interval $(0, 0.1]$ of the correlation

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[3] The fixed effects control for the situations specific to the municipal units: presences of railway and boulevard, topographic feature, and levels of EMS and FS, etc.

[4] The GMM(ex) estimator is consistent, provided that the explanatory variable x_{it} is strictly exogenous instead of being predetermined. The additional moment conditions used in the GMM(ex) estimator are a variant of those proposed by Crépon and Duguet (1997).

[5] The number of fatalities is the number of people who die in 24 hours after the occurrence of traffic accidents. In addition, it should be noted that the data of the number of traffic fatalities is based on the calendar year, while the data of the GMP is based on the fiscal year.

[6] The dataset is obtained at December 2006. The address at the time of March 2010 is http://www.pref.fukuoka.lg.jp/dataweb/

coefficients. The municipalities whose first-order serial correlation coefficients are 0.5 and above in the data of fatalities are ruled out in order to keep the coefficient γ in equation (1) from widely varying according to the municipalities. After the elimination, the number of municipalities reduces to 90 in the period used in the estimations.[7]

The descriptive statistics of the dataset for the 90 municipalities are shown in Table 1, where the statistics of $\ln GMP$ and fatalities are calculated in the span 1990-2003 and in the span 1969-2003, respectively. It should be noted that the scale of the natural logarithm of GMP ($\ln GMP$) is changed by deducting the overall mean of $\ln GMP$ from all the variables of $\ln GMP$. Accordingly, the variable $\ln GMP$ now contains both negative and positive values.[8]

The scatter plot of logarithms of the time series averages of GMP in the span 1990-2003 versus logarithms of the time series averages of fatalities in the span 1969-2003 (which uses the 90 municipalities) is depicted in Figure 1b. The scatter plot suggests the positive relationship between the GMP and the fatalities, at least on a cross-sectional basis.

In contrast, the scatter plot of logarithms of the cross-section averages of GMP using the 90 municipalities versus logarithms of the cross-section averages of fatalities using the 90 municipalities for the period 1990-2003 seems to suggest the negative relationship between the GMP and the fatalities, looking at Figure 1c. It seems likely that this is due to the temporal advances of EMS and FS. It seems unlikely that this plot represents the relationship between size of economic activity and traffic fatalities.

4. Estimation Results

In this section, the estimation results are presented for the spans in the period 1990-2003. Tables 2a and 2b exhibit the estimation results in the span 1991-1998 and in the span 1996-2003, respectively. In both spans, the Sargan test statistics say that the model is correctly specified and the moment restrictions used are valid. Further, the qd1 and qd2 test statistics show evidences that there is no serial correlation in the disturbance in equation (1) and that the explanatory variable is predetermined.[9] In Appendix B, the qd1 and qd2 tests are described in detail. In addition, it is conceivable that the t-values for the estimated parameters obtained by using the GMM estimators are biased upwards, making the comparison between Monte Carlo standard deviation and Monte Carlo mean of standard error in the Monte Carlo results by Kitazawa (2007).[10] Accordingly, it is desirable to keep in mind that the problem of the upward biased t-values is able to arise in the use of the GMM estimators, when the inferences are conducted.

Figures 2a and 2b also present the relationships between the length of the pre-sample history and the PSM estimates. It is shown that the PSM estimates gradually decrease with the increase of the length of pre-sample history and subsequently remain virtually steady.

From now on, the examination is conducted on the result for the span 1991-1998, referring to Table 2a. Judging from the Monte Carlo results conducted by Blundell et al. (2002) and Kitazawa (2007), it is expected that the true values of γ and β are below the Level estimates (0.252, 0.663) and above the WG estimates (-0.190, -0.860), respectively. The GMM(qd) and GMM(ex) estimates of β are negative and far below the WG estimate. The GMM(qd) estimate seems to suffer from the problem of the downward bias in small sample, while the negative estimate of β by the GMM(ex) estimator seems to be due to the usage of the moment conditions valid only under

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[7] See Appendix A for the municipalities composing the dataset and used in the estimation.

[8] This is a requirement for using the GMM(pr), GMM(sa) and GMM(sb) estimators. On detail, see Wooldridge (1997), Windmeijer (2000, 2008), Kitazawa (2007) and Winkelmann (2008).

[9] For GMM(ex) estimator, these test statistics show evidences that there is no serial correlation in the disturbance in equation (1) and that the explanatory variable is strictly exogenous.

[10] It may be that the finite sample variance correction proposed by Windmeijer (2005, 2008) improves the upward bias of the t-values.

the assumption of the strictly exogenous explanatory variables.[11] The GMM(sa) and GMM(sb) estimates and the PSM estimates with length of pre-sample used being 22 are below the Level estimate and above the WG estimate. Firstly, in consideration of Figure 1a in previous section, it seems that these estimates of γ is in accordance with the suggestion from the histogram of the first-order serial correlation coefficients. Accordingly, it is likely that regarding the true value of γ as being zero is permissible. Next, in light of Figure 1b in previous section, the GMM(sa) and GMM(sb) estimates (0.649 and 0.557 respectively) for β are near to the estimated coefficient (0.762) of the regression equation in Figure 1b, compared to the PSM estimate (0.210). It may be said that since the data points are located near the regression line in almost all cases, the value of β of the Level estimate is near to the value of the estimated coefficient of the regression line and therefore these values are within touch of the true values of β. Accordingly, it seems reasonable to consider that the true value of β is close to the GMM(sa) and GMM(sb) estimates.[12] It is likely that the PSM estimate is afflicted with the problem of the endemic downward bias originating when the fixed effect composing the explanatory variable is not proportional to the fixed effect in the count regression for each individual, as pointed out in Kitazawa (2007).

The examination similar to that for the span 1991-1998 is able to be applied to the case for the span 1998-2003, looking at Table 2b. The exception is the GMM(qd) estimate (0.304) of β, which is below the Level estimate and above the WG estimate certainly. However, the t-value (0.744) for the GMM(qd) estimate of β is considerably small and therefore the GMM(qd) estimate of β is not significant at conventional level.[13] In this case, the GMM(sa) and GMM(sb) estimators generate the plausible estimates of γ and β, which are -0.030 and 0.602 for the GMM(sa) estimator and -0.094 and 0.431 for the GMM(sb) estimator.

The elasticity of the fatalities with respect to the GMP is calculated using the estimation results. Since the value of γ seems to be zero, the long-run elasticity is able to be regarded as being equal to the short-run elasticity (see Appendix C). Accordingly, it is conceivable that the elasticity is located near 0.5, based on the GMM(sa) and GMM(sb) estimates. It can be said that the elasticity assessed comprehensively from the estimation results above is positive and below unity, which implies decreasing return to scale and is considered to be convincing. The diseconomy of scale suggests that the larger size of economic activity is more desirable for the traffic safety, at least in terms of the shrinkage of the traffic fatalities.

5. Conclusion

In this paper, the relationship between the fatalities due to traffic accidents and the GMP was investigated in the framework of the LFM for count panel data, by using panel data of municipalities in Fukuoka Prefecture in Japan. The investigation was conducted as an application of some GMM estimators newly proposed by Kitazawa (2007). The results say that the conventional GMM(qd) estimator proposed by Chamberlain (1992) and Wooldridge (1997) generated unconvincing results (negative estimate and insignificant estimate of coefficient on logarithm of the scaled GMP), while some of the GMM estimators newly proposed by Kitazawa (2007) (i.e. the GMM(sa) and GMM(sb) estimators) generated convincing results (estimates being positive and below unity). The former results imply that the larger size of economic activity brings about the less

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[11] It seems that the negative GMM(ex) estimate of β arises from the ignorance of the possibility that the current traffic fatalities affect the future GMP in each municipality. Accordingly, it is just proper to suppose that the GMP is not strictly exogenous but predetermined. When the investigations are conducted on relationships between occurrences of traffic accidents and indexes associated with the economic activity, alert needs to be enormously raised over the assumption that the indexes are strictly exogenous.

[12] Although the GMM(pr) estimate (0.860) is near the value of the estimated regression coefficient, it is above the Level estimate. However, the fact that it is positive is unchanged.

[13] Furthermore, allowing for the problem of the upward biased t-values, it is considerably difficult to say that the GMM(qd) estimate of β is significant.

number of traffic fatalities or that the traffic fatalities are not related to size of economic activity, while the latter ones suggest the reverse association and the diseconomy of scale in the occurrence of traffic fatalities.

Appendix A

The dataset in this paper is composed of the following municipalities with the codes in this paper: 1. Kitakyushu, 2. Fukuoka, 3. Omuta, 4. Kurume, 5. Nogata, 6. Iizuka, 7. Tagawa, 8. Yanagawa, 9. Yamada, 10. Amagi, 11. Yame, 12. Chikugo, 13. Okawa, 14. Yukuhashi, 15. Buzen, 16. Nakama, 17. Ogori, 18. Chikushino, 19. Kasuga, 20. Onojo, 21. Munakata, 22. Dazaifu, 23. Maebaru, 24. Koga, 25. Nakagawa, 26. Umi, 27. Sasaguri, 28. Shime, 29. Sue, 30. Shingu, 31. Hisayama, 32. Kasuya, 33. Fukuma, 34. Tsuyazaki, 35. Oshima, 36. Ashiya, 37. Mizumaki, 38. Okagaki, 39. Onga, 40. Kotake, 41. Kurate, 42. Miyata, 43. Wakamiya, 44. Keisen, 45. Inatsuki, 46. Usui, 47. Kaho, 48. Chikuho, 49. Honami, 50. Shonai, 51. Kaita, 52. Haki, 53. Asakura, 54. Miwa, 55. Yasu, 56. Koishiwara, 57. Hoshuyama, 58. Nijo, 59. Shima, 60. Yoshii, 61. Tanushimaru, 62. Ukiha, 63. Kitano, 64. Tachiarai, 65. Jojima, 66. Oki, 67. Mizuma, 68. Kurogi, 69. Joyo, 70. Tachibana, 71. Hirokawa, 72. Yabe, 73. Hoshino, 74. Setaka, 75. Yamato, 76. Mitsuhashi, 77. Yamakawa, 78. Takata, 79. Kawara, 80. Soeda, 81. Kaneda, 82. Itoda, 83. Kawasaki, 84. Akaike, 85. Hojo, 86. Oto, 87. Aka, 88. Kanda, 89. Saigawa, 90. Katsuyama, 91. Toyotsu, 92. Shiida, 93. Yoshitomi, 94. Tsuiki, 95. Shin-yoshitomi, 96. Taihei. In the estimations, the following municipalities are ruled out: 1. Kitakyushu, 2. Fukuoka, 3. Omuta, 6. Iizuka, 90. Katsuyama, 92. Shiida.

Appendix B

Arellano and Bond (1991) construct the first-order and second-order serial correlation test statistics in the context of the dynamic panel data model. In addition, B. H. Hall constructs the similar serial correlation test statistics at 1997. As is similar to the case for ordinary panel data models including the dynamic panel data model, it is possible to construct the test statistics related to the serial correlations in residuals for the count panel data model. Windmeijer (2002) provides the serial correlation test statistics for the count panel data model in his package "ExpEnd" written by Gauss, which are an extension of those in Arellano and Bond (1991). In this paper, another serial correlation test statistics for the count panel data model are used, which are an extension of those proposed by B.H. Hall.

If the assumption (2) holds for the model (1), the following relationship holds for the quasi-differenced transformation:

$$E[p_{it} p_{i,t-2}]=0 \quad , \qquad \text{for} \quad t=5,\ldots,T \quad , \tag{B1}$$

where $p_{it}=u_{it}(\mu_{i,t-1}/\mu_{it})-u_{i,t-1}$ with $\mu_{it}=\exp(\beta x_{it})$ and $u_{it}=y_{it}-\gamma y_{i,t-1}$. Noting that the quasi-differenced transformation is rewritten as $p_{it}=v_{it}(\mu_{i,t-1}/\mu_{it})-v_{i,t-1}$ and using the relationships obtained from the assumption (2), the relationship (B1) is obtained.

Based on the relationship (B1), it is possible to design the following test statistic:

$$qd_2=\bar{m}_2/(s_2^2/h_2)^{0.5} \;\; \tilde{a} \;\; N(0,1) \quad , \tag{B2}$$

where $\bar{m}_2$ and s_2^2 are sample analogues of $E[p_{it} p_{i,t-2}]$ and $Var[p_{it} p_{i,t-2}]$ respectively, with h_2 being a sample size of $p_{it} p_{i,t-2}$. The qd2 statistic tests for the lack of second-order serial correlation in the quasi-differenced residuals. Impossibility of the rejection of the lack of second-order serial correlation by qd2 statistic manifests the validity of the assumption (2) (i.e. the serially uncorrelated disturbance and the predetermined explanatory variable in model

(1), roughly speaking).

However, the following qd1 test statistic should reject the lack of first-order serial correlation when the assumption (2) holds for the model (1):

$$qd_1=\bar{m}_1/(s_1^2/h_1)^{0.5}\ \tilde{a}\ \ N(0,1)\ \ , \tag{B3}$$

where $\bar{m}_1$ and s_1^2 are sample analogues of $E[p_{it}p_{i,t-1}]$ and $Var[p_{it}p_{i,t-1}]$ respectively, with h_1 being a sample size of $p_{it}p_{i,t-1}$. This is because $E[p_{it}p_{i,t-1}]\neq 0$ for $t=4,\ldots,T$.

It can be said that if the assumption (2) is valid in the model (1), the qd1 statistic rejects the null of the lack of first-order serial correlation in the quasi-differenced residuals, while the qd2 statistic does not reject the null of the lack of second-order serial correlation in the quasi-differenced residuals. By using these statistics, it is possible to judge whether the assumption (2) is valid or not.

After calculating the GMM(ex) estimate, the qd1 and qd2 test statistics are calculated by using the different type of quasi-differenced residuals: $e_{it}=u_{it}-(\mu_{it}/\mu_{i,t-1})u_{i,t-1}$. In this case, these turn out to be the test statistics related to the serially uncorrelated disturbance and the strictly exogenous explanatory variable in the model (1).

In Tables 2a and 2b, the qd2 statistic is calculated using the sample analogues $\bar{m}_2=(1/h_2)\sum_{i=1}^{N}\sum_{t=5}^{T}p_{it}p_{i,t-2}$ and $s_2^2=(1/(h_2-1))\sum_{i=1}^{N}\sum_{t=5}^{T}(p_{it}p_{i,t-2}-\bar{m}_2)^2$ and the sample size $h_2=N(T-4)$, while the qd1 statistic is calculated using the sample analogues $\bar{m}_1=(1/h_1)\sum_{i=1}^{N}\sum_{t=4}^{T}p_{it}p_{i,t-1}$ and $s_1^2=(1/(h_1-1))\sum_{i=1}^{N}\sum_{t=4}^{T}(p_{it}p_{i,t-1}-\bar{m}_1)^2$ and the sample size $h_1=N(T-3)$. However, it cannot be said that these sample analogues are amply preferable, since both $p_{it}p_{i,t-2}$ and $p_{it}p_{i,t-1}$ are serially correlated. Reformed types of the qd2 and qd1 statistics are calculated by using the sample size N , which are based on the standpoint that the above sample analogues for the qd2 and qd1 statistics are adjusted in time spans $T-4$ and $T-3$, respectively. The reformed qd1 and qd2 statistics are calculated by dividing the qd2 and qd1 statistics in Table 2a and 2b by $\sqrt{4}$ and $\sqrt{5}$ respectively. The reformed qd1 and qd2 statistics also say that the model and the moment conditions are valid, judging from the conventional level.

It is not difficult to calculate these test statistics by using the procedure file “lm2test.tsp” in the econometric software TSP whose manual is written by Hall and Cummins (2006). This procedure is made by B. H. Hall and revised by C. Cummins at 1997, which is able to be downloaded from the following website at the time of March 2010:

http://www.stanford.edu/~clint/tspex/

Appendix C

For the LFM, the long-run and short-run elasticities are proposed by Blundell et al. (2002), both of which are calculated as follows.

In the long-run time frame, it is assumed that the dependent and explanatory variables and the disturbance are in the steady state. This implies that $\bar{y}_i=y_{it}=y_{i,t-1}$, $\bar{x}_i=x_{it}=x_{i,t-1}$, and $v_{it}=0$. In the long-run, equation (1) reduces to

$$(1-\gamma)\bar{y}_i=\exp(c+\beta\bar{x}_i+\eta_i)\ \ . \tag{C1}$$

Taking logarithm of (C1) and transposing $\ln(1-\gamma)$ to the right-hand side,

$$\ln \bar{y}_i = -\ln(1-\gamma) + c + \beta \ln \bar{X}_i + \eta_i \quad , \tag{C2}$$

where $\bar{X}_i$ is the scaled GMP for municipality i in the steady state. This is because $X_{it} = \exp(x_{it})$ and $\bar{X}_i = X_{it} = X_{i,t-1}$ when $\bar{x}_i = x_{it} = x_{i,t-1}$. Accordingly, the long-run elasticity is

$$\partial \ln \bar{y}_i / \partial \ln \bar{X}_i = \beta \quad . \tag{C3}$$

The short-run elasticity is defined as the elasticity of y_{it} with respect to X_{it} at the neighborhood of the steady state variables $\bar{y}_i$ and $\bar{X}_i$. That is,

$$\partial \ln y_{it} / \partial \ln X_{it} \; |_{(y_{it}=\bar{y}_i,\, X_{it}=\bar{X}_i)} = (\partial y_{it} / \partial X_{it} \; |_{(y_{it}=\bar{y}_i,\, X_{it}=\bar{X}_i)})(\bar{X}_i / \bar{y}_i) \quad . \tag{C4}$$

For equation (1),

$$\partial y_{it} / \partial X_{it} = \beta X_{it}^{\beta-1} \phi_i C \quad , \tag{C5}$$

where $\phi_i = \exp(\eta_i)$ and $C = \exp(c)$, while for equation (C1),

$$\bar{X}_i / \bar{y}_i = (1-\gamma) / (\bar{X}_i^{\beta-1} \phi_i C) \quad . \tag{C6}$$

Plugging (C5) and (C6) into (C4), the short-run elasticity is

$$\partial \ln y_{it} / \partial \ln X_{it} \; |_{(y_{it}=\bar{y}_i,\, X_{it}=\bar{X}_i)} = (1-\gamma)\beta \quad . \tag{C7}$$

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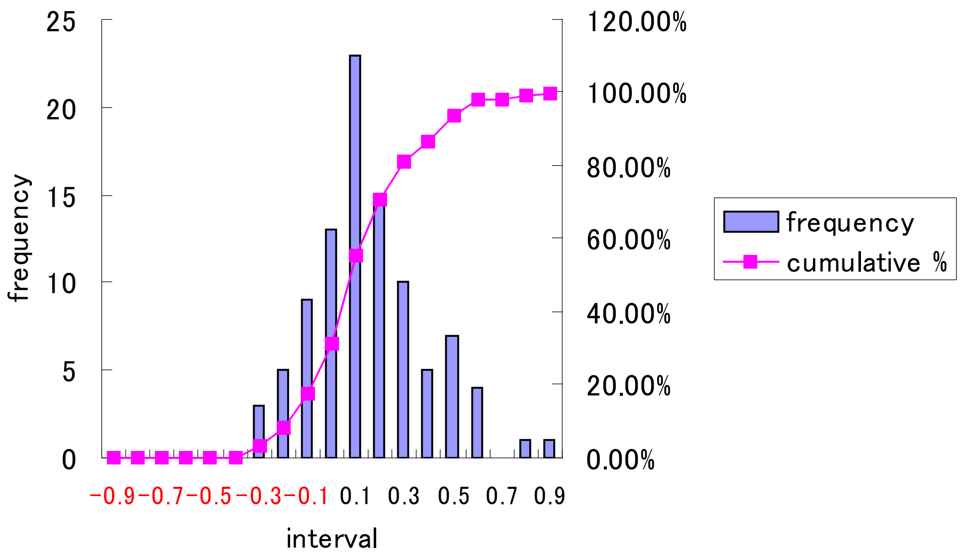


Figure 1a. Histogram of correlation coefficients

Note: The histogram is for the first-order serial correlation coefficients with respect to the numbers of fatalities in the 96 municipalities.

Table 1.
The data of GMP and fatalities in overall dataset

Number of municipal units	90	90
Period	1990-2003	1969-2003
	ln GMP	Fatalities
Mean	0.000	2.341
S.D.	1.087	2.801
Median	-0.104	2
Minimum	-2.869	0
Maximum	3.028	28
Proportion of positives	0.466	
Proportion of zeros		0.253

Note: Note: The $\ln GMP$ is the logarithm of GMP scaled by subtracting 10.570 from the original logarithm of GMP.

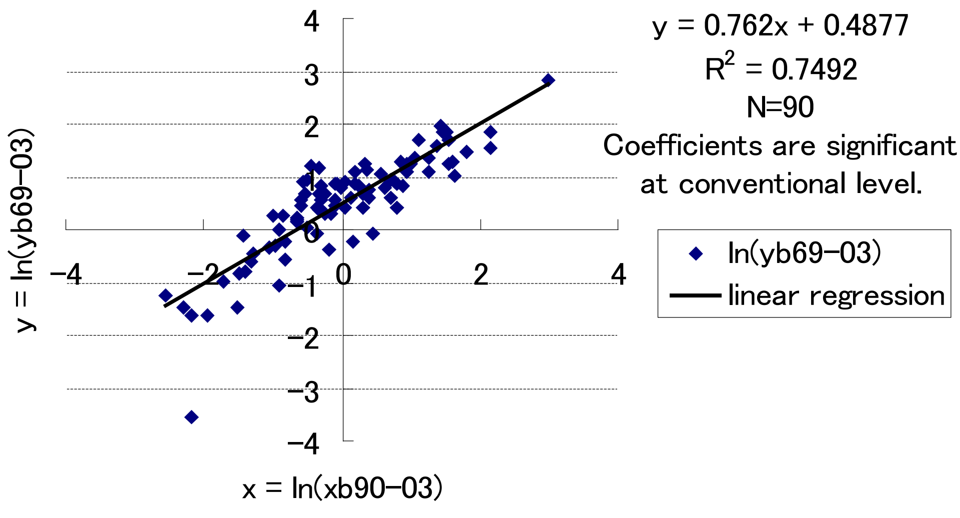


Figure 1b. Scatter plot of logarithms of time series averages

Note: The graph is the scatter plot of logarithms of the time series averages of GMP in the span 1990-2003 (x) versus logarithms of the time series averages of fatalities in the span 1969-2003 (y) for the 90 municipalities. The similar graph and relationship are obtained, even when logarithms of the time series averages of fatalities in the span 1990-2003 are used instead of those in the span 1969-2003.

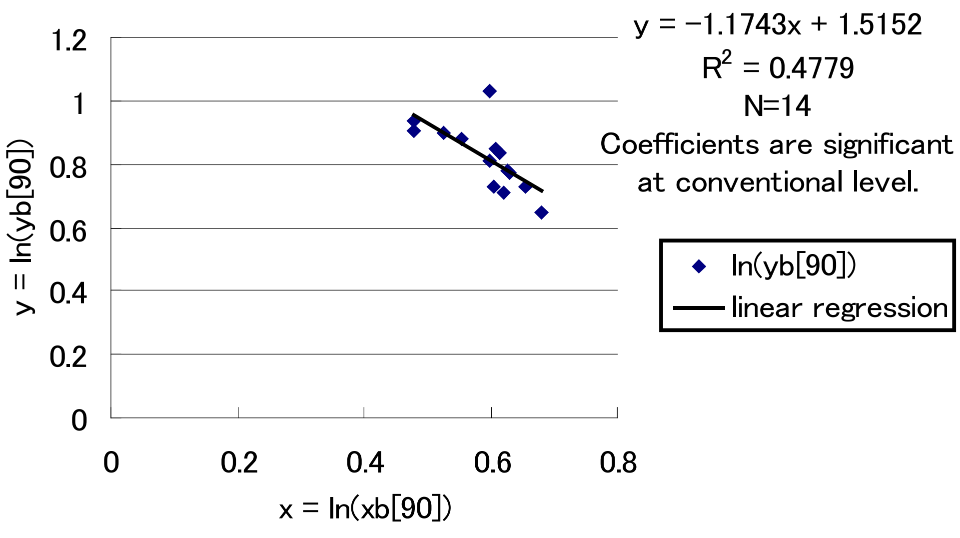


Figure 1c. Scatter plot of logarithms of cross-section averages

Note: The graph is the scatter plot of logarithms of the cross-section averages of GMP using the 90 municipalities (x) versus logarithms of the cross-section averages of fatalities using the 90 municipalities (y) for the period 1990-2003.

Table 2a.
Results for Linear Feedback Model
N=90 T=8 (span 1991−1998)

	Coeffficient		t−value		Sargan	df	p−value	qd1	qd2
	Fatalities(−1)	ln GMP	Fatalities(−1)	ln GMP					
Level	0.252	0.663	4.387	15.365					
WG	−0.190	−0.860	−1.522	−0.095					
GMM(qd)	−0.163	−2.129	−7.300	−6.217	45.390	46	0.498	−4.912	−1.398
GMM(pr)	−0.118	0.860	−7.050	9.145	50.434	51	0.496	−5.000	−0.731
GMM(ex)	0.236	−8.084	33.792	−39.427	74.691	72	0.391	−6.584	0.410
GMM(sa)	0.107	0.649	7.149	13.773	73.815	59	0.093	−5.863	0.333
GMM(sb)	−0.050	0.557	−3.679	13.419	73.448	59	0.098	−5.326	−0.385
PSM(22)	0.090	0.210	1.452	3.723					

Notes: (i) Except for the GMM(ex) estimator, the GMM estimators use the lagged dependent variables dated $t-2$ and before and the lagged explanatory variables dated $t-1$ and before as the instruments for the quasi-differenced equations dated t in the span. The GMM(ex) estimator uses the lagged dependent variables dated $t-2$ and before and the all lagged and lead explanatory variables as the instruments. (ii) The PSM estimator in the tables uses the longest length of pre-sample history available in the span, which is described in the parenthesis next to PSM. (iii) The coefficients "Fatalities(-1)" and "ln GMP" and their t-values correspond to the estimates for γ and β in equation (1). (iv) Sargan is the test statistic of over-identifying restrictions, next to which degree of freedom (df) and p-value are listed. (v) The qd1 and qd2 are the test statistics of first-order and second-order serial correlations in quasi-differenced residuals. (vi) The econometric software TSP is used in a series of estimations.

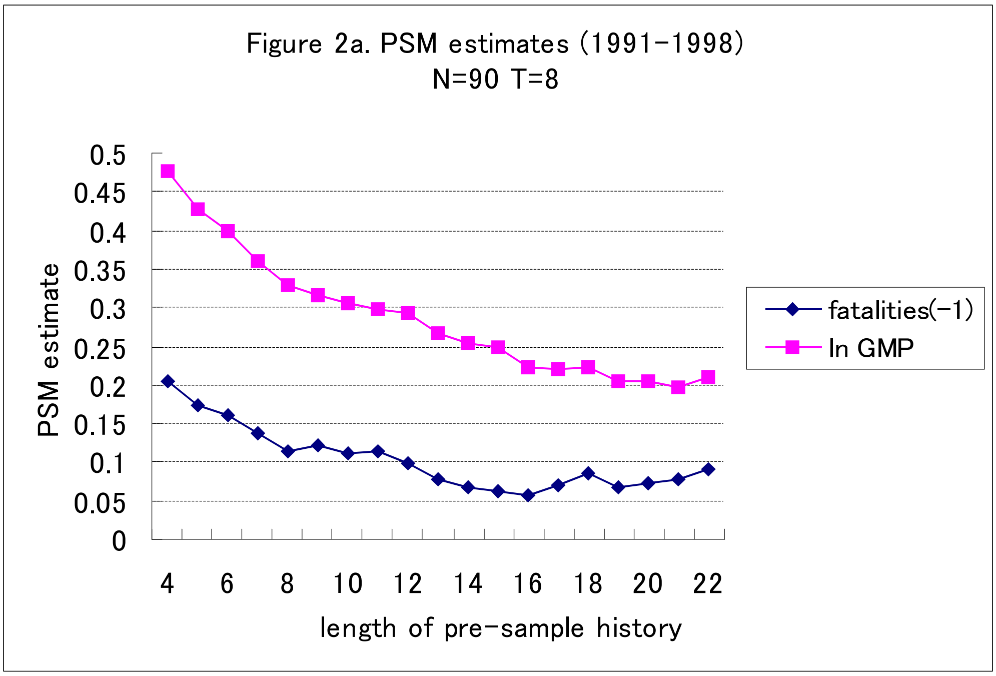


Figure 2a. PSM estimates (1991−1998)
N=90 T=8

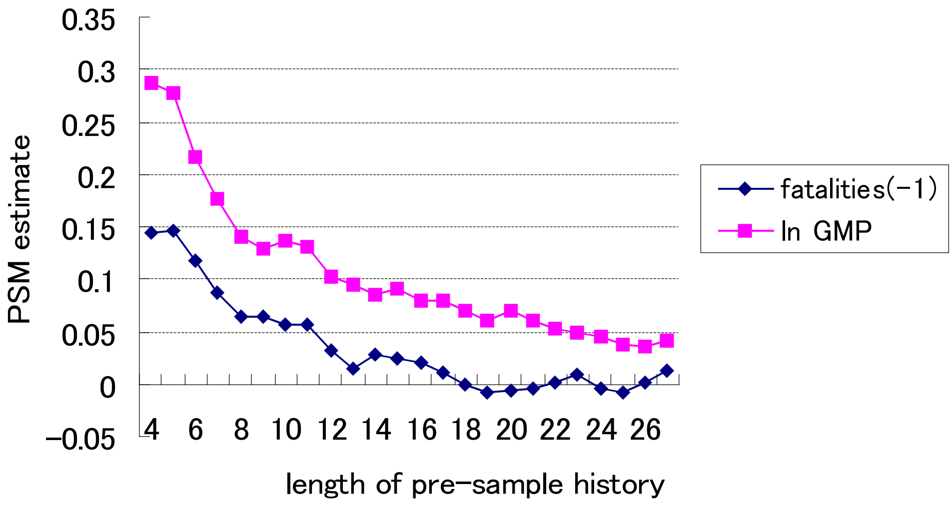
Note: The coefficients "Fatalities(-1)" and "ln GMP" correspond to the estimates of γ and β in equation (1).

Table 2b.
Results for Linear Feedback Model
N=90 T=8 (span 1996-2003)

	Coeffficient		t-value		Sargan	df	p-value	qd1	qd2
	Fatalities(−1)	ln GMP	Fatalities(−1)	ln GMP					
Level	0.251	0.604	4.608	13.805					
WG	−0.181	−0.009	−1.081	−0.001					
GMM(qd)	−0.150	0.304	−6.134	0.744	48.433	46	0.375	−4.578	−1.505
GMM(pr)	−0.164	0.703	−7.132	7.328	53.005	51	0.397	−4.498	−1.533
GMM(ex)	0.003	−1.588	0.249	−12.197	74.188	72	0.407	−5.280	−0.959
GMM(sa)	−0.030	0.602	−1.658	10.277	66.755	59	0.228	−5.049	−0.981
GMM(sb)	−0.094	0.431	−6.928	15.900	71.188	59	0.133	−4.803	−1.253
PSM(27)	0.013	0.041	0.215	0.817					

Notes: (i) Except for the GMM(ex) estimator, the GMM estimators use the lagged dependent variables dated $t-2$ and before and the lagged explanatory variables dated $t-1$ and before as the instruments for the quasi-differenced equations dated t in the span. The GMM(ex) estimator uses the lagged dependent variables dated $t-2$ and before and the all lagged and lead explanatory variables as the instruments. (ii) The PSM estimator in the tables uses the longest length of pre-sample history available in the span, which is described in the parenthesis next to PSM. (iii) The coefficients "Fatalities(-1)" and "ln GMP" and their t-values correspond to the estimates for γ and β in equation (1). (iv) Sargan is the test statistic of over-identifying restrictions, next to which degree of freedom (df) and p-value are listed. (v) The qd1 and qd2 are the test statistics of first-order and second-order serial correlations in quasi-differenced residuals. (vi) The econometric software TSP is used in a series of estimations.

Figure 2b. PSM estimates (1996-2003)
N=90 T=8



Note: The coefficients "Fatalities(-1)" and "ln GMP" correspond to the estimates of γ and β in equation (1).