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POTENTIAL FALLACIES IN MEASURING THE SAFETY EFFECTS OF ROAD ACCIDENT PREVENTION POLICES WITH DIFFERENT OBSERVATIONAL PERIODS[1]

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Abstract: This paper presents an empirical example to demonstrate that how profoundly the temporal variation of the policy effect can affect the results of measuring the safety effect of an intervention policy by using different lengths of study periods. The potential fallacies of applying the pair-t test, causal factor analysis model with dummy specification, and causal factor analysis model with time-based specification to measure the policy effect by using different prior and post implementation periods are demonstrated. The policy of criminal sanction for drunk driving in Taipei City is used as an empirical example. The results indicate the different choice of the lengths of the prior and post implementation periods would obtain the different sizes of the policy effect. Finally, the findings provide a set of valuable information for policy evaluation and alert the analysts to interpret their evaluation results carefully to avoid making an inappropriate conclusion.

Key Words: road accident prevention, temporal effect, causal factor analysis, drunk driving

1. INTRODUCTION

The confounding factors as well as the temporal variation of the policy effect may affect the validity of the results for the observational before-and-after studies in evaluating the effects of the road safety measures *(Hauer, 1997; Elvik, 2002; Chang and Yeh, 2003)*. The confounding issues have been widely recognized, and the causal factor analysis and comparison group methods have been applied to control the confounding in relevant studies *(Hauer, 1997; Elvik, 2002)*. However, few studies have been devoted into the discussion concerning the influence of the temporal variation of the policy effect.

The effects of safety measures on accident reduction may vary over time due to changes in the enforcement efforts, the design of the measures, and changes in public attention or social norms over time (*Hauer, 1997; Roger et al., 1994; DeYoung, 2000; Chang and Yeh, 2004*). In our previous paper in *Accident Analysis and Prevention 36(5)*, the temporal variation of the safety effect of road accident prevention polices has been found. However, neglecting the temporal variation of polices may induce some potential fallacies. Such fallacies may bring some inaccurate results in measuring the effect of road accident prevention polices.

Due to its mathematical simplicity, pair-t test has been commonly used in evaluating the effect of a preventive policy on reducing traffic accidents. The average accident frequencies

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(or accident rates) before and after implementing the intervention policy are collected respectively, and the pair-t test is then applied to determine whether these two average values are significantly different or not. However, two problems may be presented when using the pair-t test to measure the safety effect of an intervention policy. First, the accident reduction cannot guarantee to be the result of the intervention policy for lack of comparison with controlled counterparts. Second, if the safety effect following the implementation of a policy is not constant over time, how long after implementation will be the right time to measure its safety effect (*Chang and Yeh, 2004*)?

The most popular tool for evaluating the safety effect of policy intervention is causal factor analysis *(Chang and Yeh, 2003; Chang and Yeh, 2004; Miaou, 1994; Dionne et al., 1995; Agresti, 1996; Sohn, 1999; Li et al., 2001)*. This type of regression model is usually estimated by the least squares or maximum likelihood estimation methods *(Agresti, 1996)*. The capability of differentiating the safety effect of policy intervention from other factors makes the causal factor analysis model superior to other models. However in the literature, the effect of a policy intervention is commonly formulated by a dummy variable in the causal factor analysis models, like the linear regression or Poisson regression models *(Chang and Yeh, 2003; Chang and Yeh, 2004; Miaou, 1994)*. It only shows the average safety effect of the intervening policy over the study period, and fails to see the temporal variation of the safety effect during its evolution process. In order to catch the temporal variation of the policy effect, Chang and Yeh *(2004)* proposed the concept of life cycle and developed a causal factor analysis model with time-based specification to catch the evolution process of implementing a drunk driving prevention policy.

Two contradictory issues are noted when measuring the safety effect of an intervention policy. That is, the randomness of accident occurrence requires that the before and after observation periods should be long enough in order to measure the safety effect of the intervention policy with sufficient statistical power. However, on the other side, the longer the before and after observation periods are used, the more possible the affecting factors will change. Thus, if we fail to manipulate this problem adequately, we might make a wrong conclusion to the effect of an intervention policy.

This paper presents how the temporal variation of the policy effect can affect the results of measuring the safety effect of an intervention policy by using different lengths of study periods before and after implementing the policy. The potential fallacies may be presented when applying the pair-t test, causal factor analysis model with dummy specification, and causal factor analysis model with time-based specification to measure the policy effect by using different prior and post implementation periods are demonstrated in this study. The policy of criminal sanction for drunk driving (CSFDD) in Taipei City was used as an empirical example for this study. Our findings would provide very valuable information for policy evaluation and alert the analysts to interpret their evaluation results carefully to avoid making an inappropriate conclusion.

Following the introduction of study background, a brief description about the policy of CSFDD in Taiwan is provided. The potential fallacies of applying the pair-t test and the causal factor analysis models with dummy-based and time-based specifications with different lengths of before and after observation periods are presented separately in the following sections. And some discussions and conclusions are made in the final section of this paper.

2. THE PREVENTIVE POLICIES AGAINST DRUNK DRIVING IN TAIWAN

In order to fight against drunk driving, a lot of effort has been devoted to deter people from driving while impaired during the past ten years. The regulations in Taiwan stipulate that drivers with breath alcohol contents higher than 0.25mg/liter will be punished by a fine of 6,000 New Taiwan dollars (NT$ 6,000, approximate US$ 190), suspension of their driver license for 6 months, and the mandatory attending of a four-hour education course until June 2001. Drunk drivers who are found guilty in a fatal traffic accident will be deprived of their rights to drive for the rest of their lives. However, this severe punishment still cannot deter people from driving while intoxicated.

Due to two fatal accidents caused by drunk drivers at the end of 1998, the public's attention was again attracted, and heated debates against drunk driving were started in the public. Those events finally brought additional regulation to deter people from driving while intoxicated, and the law of "criminal sanction for drunk driving" (CSFDD) was enacted in May 1999. Under the new regulation, drivers with breath alcohol contents higher than 0.55mg/liter will be fined up to NT$ 90,000(approximate US$2,800), put into prison (up to 1 year), and suspended their driver licenses for up to three years.

Though the CSFDD policy was enacted to punish the drunk drivers with the breath alcohol contents higher than 0.55 mg/liter, it also deters the potential offenders from driving while intoxicated, even with breath alcohol under 0.55 mg/liter. Therefore, the CSFDD is expected to reduce the number of fatal accidents involved drunk drivers not only with the breath alcohol content higher than 0.55 mg/liter, but also with breath alcohol content between 0.25 and 0.55 mg/liter. Thus, the effect of the CSFDD policy is measured by the reduction of drunk driving fatal accidents that involved drivers who were found guilty for the accidents and had breath alcohol contents higher than 0.25mg/liter.

3. POTENTIAL FALLACIES OF APPLYING PAIR-T TESTS TO MEASURE THE POLICY EFFECT

In the pair-t test approach, the average accident frequencies (or accident rates) before and after implementing the intervention policy are collected respectively, and the pair-t test is then applied to determine whether these two average values are significantly different or not. All factors except implementing the new policy are assumed the same for both the observation periods before and after implementation of the policy. As mentioned in previous section, the analysts will face the problem about how long the observation periods before and after implementing the policy should be used for applying the pair-t test to measure the safety effect of the policy? Different observation periods might bring about different conclusion to the effectiveness of the implemented policy.

In order to demonstrate this potential fallacy in measuring the effect of a preventive policy, one empirical example of the policy for reducing drunk driving in Taipei City is used in this study. Fifty-eight monthly statistics for fatal accidents involved by drunk driving in Taipei City, from March 1996 to December 2000, were collected to perform the following demonstrations. The monthly counts for fatal accidents were shown in Table 1. For convenience, each month was designated with a series number in numerical order. That is, the first month of March 1996 was the 1st observation month and the last month of December 2000 was the 58th observation month in this study. The CSFDD policy has been implemented since the 39th observation month.

Table 1 The monthly Counts for Drunk Driving Related Fatal Accidents During March,1996 and December, 2000 in Taipei City

No.	Month/Year	Counts	No.	Month/Year	Counts	No.	Month/Year	Counts
1	03/96	2	21	11/97	7	41	07/99	1
2	04/96	5	22	12/97	1	42	08/99	0
3	05/96	3	23	01/98	3	43	09/99	0
4	06/96	2	24	02/98	0	44	10/99	1
5	07/96	4	25	03/98	1	45	11/99	0
6	08/96	2	26	04/98	0	46	12/99	0
7	09/96	6	27	05/98	0	47	01/00	1
8	10/96	5	28	06/98	0	48	02/00	2
9	11/96	2	29	07/98	0	49	03/00	1
10	12/96	4	30	08/98	2	50	04/00	2
11	01/97	0	31	09/98	4	51	05/00	3
12	02/97	3	32	10/98	1	52	06/00	3
13	03/97	1	33	11/98	2	53	07/00	2
14	04/97	1	34	12/98	3	54	08/00	2
15	05/97	3	35	01/99	4	55	09/00	2
16	06/97	1	36	02/99	1	56	10/00	2
17	07/97	1	37	03/99	1	57	11/00	4
18	08/97	0	38	04/99	1	58	12/00	0
19	09/97	0	39**	05/99	1			
20	10/97	1	40	06/99	1			

Note: this table was adopted from Chang and Yeh (2003).

The example of evaluating the effect of the CSFDD in Taipei City by using pair-t test is introduced in this study for comparison purpose. The means and variances of the monthly drunk driving fatal accidents occurred within the 5, 10, 15, and 20 months after the implementation of the CSFDD are showed respectively in Table 2. The CSFDD was introduced with major penalties and considerable public attention, so the effect of CSFDD is expected to be a rapid initial response followed by a period of decay with slower decreasing rate. The statistical results show the longer observation periods after implementing CSFDD experienced higher means and variances of monthly drunk driving fatal accidents. It also implied the effect of CSFDD dissipated gradually as expected. Hence, the longer observation periods after implementation are applied to measure the effect of CSFDD, the lower effect of CSFDD will be obtained.

On the other hand, the means and variances of the monthly fatal drunk driving accidents for different observation periods before implementing CSFDD are also showed in Table 2. According to the statistical results showed in Table 2, we can find a U-shaped trend for the averaged monthly fatal drunk driving accidents during the observation periods before implementing CSFDD. However, the longer observation periods seemed not to have smaller variances than the short observation periods as expected. It might be the case that some other affecting factors were involved to the occurrence of fatal drunk driving accidents.

When we compared the 5-month and 10-month post implementation periods with all the eight prior implementation periods respectively, we found the effects of the CSFDD were all significant. The average monthly drunk driving fatal accidents of the 15-month post implementation period was found significantly lower than those of 5-month, 10-month, 35-month and 38-month prior implementation periods, but not significantly lower than those of 15-month, 20-month, 25-month, and 30-month prior implementation periods. Finally, the mean value of the monthly drunk driving fatal accidents for the 20-month post implementation period was not significantly lower than those of all the prior implementation periods as showed in Table 2 except for the 38-month prior implementation period.

Table 2 Pair-t Statistics for Before-and-After Comparisons For the CSFDD by Using Different Observation Periods.

Number of months before implementing CSFDD (Mean, Variance)	Number of months after implementing CSFDD (Mean, Variance)			
	5 (0.600, 0.300)	10 (0.700, 0.456)	15 (1.200, 1.029)	20 (1.400, 1.305)
5 (2.000, 2.000)	2.064**	1.947 *.	1.389 *	1.005
10(1.900, 1.878)	2.611**	2.484**	1.470 *	1.058
15(1.333, 1.952)	1.451 *	1.510 *	0.298	-0.156
20(1.600, 3.305)	2.107**	1.960**	0.827	0.417
25(1.520, 2.843)	2.207**	2.054**	0.749	0.284
30(1.600, 2.731)	2.573**	2.435**	1.001	0.506
35(1.914, 3.316)	3.340**	3.241**	1.767**	1.285
38(2.026, 3.324)	3.713**	3.635**	2.091**	1.602 *

* Significant at α=0.10 ** Significant at α=0.05

According to the study results of the pair-t tests of the above empirical examples, the length choices of the prior and post implementation periods are critical not only to determine the statistical significance of policy effect but also to measure the amount (or proportion) of accident reduction brought by the policy. However, for the case of CSFDD, the length choice for the post implementation periods seems to be more sensitive than that for the prior implementation periods in measuring the safety effect of CSFDD by pair-t tests.

4. POTENTIAL FALLACIES OF APPLYING THE CAUSAL FACTOR ANALYSIS METHOD WITH A DUMMY VARIABLE TO MEASURE THE POLICY EFFECT

Pair-t tests could not measure the policy effect adequately because its optimistic assumption that the other factors keep constantly over the whole study time period, except for the policy intervention. The potential fallacies in measuring the policy effect by pair-t approach have been introduced in the previous section. The causal factor analysis methods that allow controlling the impacts of the other factors are expected to measure the policy effect much better than pair-t tests. In convention, the policy intervention is commonly represented by a dummy variable to catch its effect on reducing the accident occurrence in the causal factor models *(Chang and Yeh, 2003; Chang and Yeh, 2004; Miaou, 1994; Voas et al., 2000).*

Poisson regression model is one of the causal factor analysis techniques. When the number of accidents that occurred in each observation interval is small, the Poisson regression models, through the maximum likelihood estimation approach, are widely used for statistical robustness. The Poisson distribution is known to describe well the random behavior of the occurrence of discrete events such as accident frequency *(Hauer, 1997; Chang and Yeh, 2003; Chang and Yeh, 2004; Agresti, 1996; Sohn, 1999)*. Poisson regression models can be employed to formulate the discrete count accident data, and to evaluate the effect of the intervention policy. The Poisson regression model is defined in terms of its density function, i.e.

$$P(y_t) = e^{-\lambda_t} \lambda_t^{y_t} \Big/ y_t! \quad (t = 1, \ldots, T) \tag{1}$$

Where y_t is the frequency of accidents that occurred in the observation interval t. The expected value of the Poisson regression model, $E(y_t) = \lambda_t$, equals the variance. In the Poisson regression models, the function of mean is specified as $\lambda_t = f(x_t, \beta)$, x_t is the vector of explanatory variables in the observation interval t and β is the corresponding parameter vector to be estimated. Generally, the function can be any functional form. However, in order to restrict the value of λ_t to be positive, the exponential function is commonly used in practice. By applying the Poisson regression model to formulate the accident occurrence over time, and to explore the effect of the intervening policy on accident reduction, we assume that the expected accident frequency occurred in the observation interval t is:

$$\lambda_t = e^{\beta_0 + \beta x_t} \tag{2}$$

Where x_t is the vector of contributing variables in the observation interval t, β is the vector of parameters to be estimated. A dummy variable is used to represent the policy effect over time after the policy was implemented.

Similarly, the drunk drinking prevention policy in Taipei is again used as an example to illustrate the causal factor analysis with representing the policy as a dummy variable in measuring the policy effect. Some additional explanatory variables were incorporated into the model formulation of causal factor analyses. Furthermore, different observation periods before and after implementing CSFDD were applied for model estimation in order to have the insight into the effect of temporal variation on evaluating the policy effect.

Some regulations on drunk driving had already been developed prior to the implementation of CSFDD, and a lot of effort had already been devoted to enforcement over the past years. Therefore, the CSFDD can be thought of as an additional treatment to enhance the effect of reducing alcohol-related fatal accidents. In order to clarify the additional effect that resulted from the CSFDD only, the effects corresponding to policies existing prior to CSFDD as well as the enforcement devotion over the whole observation period should be effectively separated in the model specifications. Police manpower or financial resources devoted to drunk driving prevention seems to be an appropriate variable to represent the devotion of enforcement. For lack of reliable data about the manpower or financial support devoted to enforcement, the number of drunk driving offenders arrested by police in the time interval t, X_{1t}, is therefore considered as the proxy explanatory variable in model specification to reflect the compound effect of existing policies and enforcement on reducing drunk driving fatal accidents.

In addition, alcohol consumption is another influencing factor in alcohol-related fatal accidents *(Chang and Yeh, 2004; Voas et al., 2000)*. Thus, including the variable of alcohol-consumption into the models is expected to avoid the potential bias in model estimations. The sales of alcohol or alcoholic beverages are usually used as a surrogate measure due to measuring the alcohol consumption for a specific city in a given time interval is difficult in practice. Furthermore, only the yearly data for beer, wine and liquor sales of Taipei City are available. Thus, the yearly alcohol sales index is incorporated into the model instead of the monthly alcohol sales index. The amount of sales of alcoholic beverages in Taipei City in

1996 is set as the alcohol sales index of 1 for comparison purpose. The values of the alcohol sales index for other years are then defined as the ratio of the amount of alcohol sales in a given year to the amount of alcohol sales in 1996. The variable of yearly alcohol sales index, X_{2t}, is served as a year-based covariate only. The detailed information concerning these data should be referred to our previous paper in Accident Analysis and Preventions (*Chang and Yeh, 2004).*

Finally, we apply the dummy variable, X_{3t}, to represent the CSFDD policy being implemented in the t^{th} month. The Poisson regression model with a dummy variable can then be formulated as equation (3).

$$\lambda_t = e^{(\beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t})} \tag{3}$$

The estimated results of causal factor analysis models with different observation periods before and after implementing CSFDD are showed in Table 3. The estimated results of the causal factor analysis models combining the 38-month and 35-month prior implementation periods (38 months) with different lengths of post implementation periods, including 5-month, 10-month, 15-month, and 20-month observation periods, showed the coefficients of both alcohol consumption and CSFDD policy were significantly different from zero. However, the coefficients of enforcement were significantly different from zero at α=0.10 only for the models combining the 38-month prior implementation periods with 5-month and 10-month post implementation periods, and marginally significantly different from zero for the other models. If we define the safety effect as the proportion of accidents reduced by CSFDD, then the safety can be measured by the factor of $(1 - e^{\beta_3 X_{3t}})$. The safety effects of CSFDD would be 0.77, 0.80, 0.74 and 0.73, if we applying the 35-month prior implementation period with 5-month, 10-month, 15-month, and 20-month post implementation periods for model estimation respectively. We might conclude that CSFDD were effective with stable safety effect over time.

When the causal factor analysis models with dummy-based specification were estimated by the 30-month prior-implementation periods with four different lengths of post-implementation periods, the coefficients of CSFDD were significantly different zero at α=0.05 for all the four models, but the coefficients of alcohol consumption were significant only for the models with 15-month and 20-month post implementation periods. The coefficients of enforcement were not significant no matter what kinds of post implementation periods were applied. The safety effects of CSFDD would be 0.71, 0.72, 0.66 and 0.66, if we applying the 30-month prior implementation periods with 5-month, 10-month, 15-month, and 20-month post implementation periods for model estimation respectively. Again, we would conclude that CSFDD were effective with stable safety effect over time.

However, when the causal factor analysis models with dummy-based specification were estimated by the 25-month and 20-month prior implementation periods with four different lengths of post implementation periods, we would find the coefficients of CSFDD were not significant for the models with 5-month post implementation periods. The coefficients of alcohol consumption are significant only for the models with 15-month and 20-month post implementation periods. The coefficients of enforcement were not significant no matter what kinds of post implementation periods were applied.

Table 3 The Estimated Results for Poisson Regression Models with a Dummy for Different

Lengths of Observation Periods (P-value in the Parenthesis)

Sample Size (Before, After)	Dummy-based Model : $\lambda_t = e^{(\beta_0+\beta_1 X_{1t}+\beta_2 X_2 t+\beta_3 X_{3t})}$					
	β_0	β_1	β_2	β_3	Log likelihood value	Safety effect
43 (38, 5)	-5.1604 (0.1545)	-0.0002 (0.0903)*	6.4865 (0.0736)*	-1.4849 (0.0164)**	-22.3426	0.77
48 (38, 10)	-5.6222 (0.1105)	-0.0002 (0.0866)*	6.9617 (0.0477)**	-1.5817 (0.0006)**	-26.5158	0.78
53 (38, 15)	-7.3593 (0.0262)**	-0.0002 (0.1326)	8.6858 (0.0084)**	-1.3422 (0.0005)**	-30.0770	0.74
58 (38, 20)	-7.5530 (0.0198)**	-0.0002 (0.1157)	8.8975 (0.0058)**	-1.2956 (0.0005)**	-33.1423	0.73
40 (35, 5)	-5.1306 (0.1579)	-0.0002 (0.1194)	6.4779 (0.0763)*	-1.4845 (0.0168)**	-24.3221	0.77
45 (35, 10)	-5.5915 (0.1122)	-0.0002 (0.1082)	6.9607 (0.0484)**	-1.5900 (0.0007)**	-28.4898	0.80
50 (35, 15)	-7.3184 (0.0269)**	-0.0002 (0.1555)	8.6754 (0.0086)**	-1.3509 (0.0006)**	-32.0582	0.74
55 (35, 20)	-7.5121 (0.0202)**	-0.0002 (0.1311)	8.8966 (0.0058)**	-1.3093 (0.0006)**	-35.1121	0.73
35 (30, 5)	-3.0974 (0.4595)	-0.0000 (0.9157)	3.7810 (0.3852)	-1.2244 (0.0611)**	-29.6083	0.71
40 (30,10)	-4.3301 (0.2671)	-0.0001 (0.7317)	5.1739 (0.1973)	-1.2750 (0.0151)**	-34.0717	0.72
45 (30,15)	-6.7132 (0.0549)*	-0.0000 (0.7698)	7.6265 (0.0317)**	-1.0794 (0.0182)**	-37.8138	0.66
50 (30,20)	-7.0574 (0.0367)**	-0.0001 (0.6495)	8.0531 (0.0186)**	-1.0643 (0.0173)**	-41.0196	0.66
30 (25,5)	-0.6814 (0.8930)	0.0000 (0.9071)	1.0796 (0.8372)	-0.9918 (0.1526)	-26.5942	0.63
35 (25,10)	-2.6713 (0.5584)	-0.0000 (0.8389)	3.3536 (0.4721)	-1.0757 (0.0577)*	-31.2989	0.66
40 (25,15)	-6.0725 (0.1227)	-0.0000 (0.9098)	6.8451 (0.0824)*	-0.9377 (0.0572)*	-35.2685	0.61
45 (25,20)	-6.4740 (0.0854)*	-0.0001 (0.7633)	7.3655 (0.0499)**	-0.9385 (0.0520)*	-38.5285	0.61
25 (20,5)	-0.3073 (0.9608)	0.0001 (0.7133)	0.4473 (0.9415)	-0.9441 (0.1753)	-21.4230	0.61
30 (20,10)	-2.6690 (0.6690)	0.0000 (.9690)	2.7690 (0.6167)	-1.0198 (0.0719)*	-26.3171	0.64
35 (20,15)	-7.1228 (0.1429)	0.0001 (0.7022)	7.5579 (0.0991)*	-0.8787 (0.0732)*	-30.2870	0.58
40 (20,20)	-7.2106 (0.1186)	0.0000 (0.8738)	7.8397 (0.0714)*	-0.8871 (0.0648)*	-33.6525	0.59

** Significant at α =0.10; ** Significant at α =0.05.*

The safety effects of CSFDD would be 0.61, 0.64, 0.58 and 0.59, if we applying the 20-month prior implementation periods with 5-month, 10-month, 15-month, and 20-month post implementation periods for model estimation respectively. When the short post implementation period is used to measure the effect of CSFDD, we might conclude that CSFDD was ineffective.

The causal factor analysis models with a dummy variable have better statistical explanatory power in measuring the policy effect than pair-t tests due to control the other influencing factors. The averaged effect of policy effect over the whole post implementation period observed makes the safety effect relatively stable over time and unlikely to appear insignificant if the effect of an intervention policy really sustains for a substantial period. However, the potential fallacy will still appear, if we do not applied appropriate prior and post implementation periods (i.e., too long or too short) for measuring the effect of an intervention policy.

5. APPLYING THE CAUSAL FACTOR ANALYSIS METHOD WITH TIME VARIABLES TO MEASURE THE POLICY EFFECT WITH DIFFERENT POST IMPLEMENTATION PERIODS

In last section, we have found the selection of both prior and post implementation periods might affect the conclusion about the significance of policy effect as well as the amount of accident reduction. Those potential fallacies might be resulted from the temporal variation of the policy effect and the missing of influencing factors in model formulation. In order to catch the temporal variation of policy effect, Chang and Yeh *(2004)* proposed the causal factor analysis models with time-based specifications as following equations of (4) and (5), and proved the temporal variation of the policy effect could be appropriately captured by using the example of CSFDD in Taipei City. In their models, the time-based variable was used instead of the dummy variable X_{3t} in the equation (3). They are

$$\lambda_t = e^{(\beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 \ln(t'+1))} \tag{4}$$

$$\lambda_t = e^{(\beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 \ln(t'+1) + \beta_4 (\ln(t'+1))^2)} \tag{5}$$

Where t' is the elapsed time since the CSFDD was started. The equation (5) is the preferred model estimated by using the 58-month observation period *(Chang and Yeh, 2004)*. The changing pattern of the CSFDD effect appeared the rapid initial response followed by a slower decay. Although the time-based Poisson regression model is able to measure the effect of the CSFDD policy from time to time during its evolution process *(Chang and Yeh, 2004)*, no evidence shows that this method could provide the suggestion concerning that how to choose the appropriate length of the observation period in measuring the effect of the policy. Therefore, the re-estimation of the models with different lengths of the observation time periods is performed to explore the ways to choose the appropriate length of observation period.

According to the results of the above sample, the length choice for the post implementation periods seems to be more sensible than that for the prior implementation periods in measuring the safety effect of the CSFDD. Therefore, this re-estimation will focus in exploring the impacts of using different post implementation periods on the effects of the CSFDD. Hence, the time-based models are estimated with the longest prior-implementation period (38 months) and twenty post implementation periods, including from 1-month to 20- month. The estimated results are summarized in Table 4. The estimated results of the models using 39-month, 40-month, and 41-month observation periods show that the values of coefficients of ln

(t'+1) and (ln (t'+1))^2 are insignificant. This is because fewer sample points of the post-implementation period have been used in model estimation. These results imply that if the analysts choose the observation period contained the very short post implementation period may see the insignificant effect of the CSFDD policy. Nevertheless, we cannot conclude that the CSFDD has ineffective effect based on the above results.

The results in Table 4 present that the values of coefficient of ln(t'+1) are significant for the models with from 42-month to 50-month observation periods. However, the values of the coefficient of (ln(t'+1))^2 are insignificant in these models. Model 1 is, therefore, preferred than Model2 over these observation periods. The effects of the policy estimated over these observation periods appear the higher size of the effect. This may imply that the policy moves into the growth stage of its evolution process. We could conclude the CSFDD has significant effect at an increasing rate during these observation periods. Nevertheless, analysts are unable to extend the above conclusion to infer that the size of the effect will be remained increasing over the following the observation period.

All of the remaining estimations for 51-month to 58-month observation periods for Model 1 and Model 2 shown in Table 4 appear significant. The estimated results of Model 2 for these observation periods are better than the Model 1 in term of their statistical explanatory abilities. However, the devotion of enforcement of Model 2 for 51-month to 57-month periods have marginally significant effects. We would choose Model 2 over Model 1 for these observation periods due to their better statistical explanatory abilities. Such results may imply that the effect of the policy start to decline over the observation periods. We might conclude that the CSFDD starts to appear decreasing effect over more than 50-month observation periods.

For comparing the changing pattern of the different lengths of observational periods from 51-month to 58-month for Model 2, the safety effect of the CSFDD can be measured by the multipliers of $(1-e^{\beta_3 \ln(t'+1)+\beta_4 (\ln(t'+1))^2})$, while other variables keep constantly (*Chang and Yeh, 2004*). The values of safety effect factors over time t’ for model 2 from 51-month to 58-month are plotted and shown in Figure 1.

Figure 1 shows the safety effect factors of different Model 2 with different observational periods from 51-month to 58-month. The safety effect factors of 8 models appear the similar pattern the increased effects sharply followed by a lower rate of decay. The results confirm the existence of the life cycle of the policy.

Table 4 The Estimated Results for Time-Based Poisson Regression Models for 39-58 Months Periods (p-value in the parenthesis)

Sample Size (Before, After)	Model 1: $\lambda_t = e^{\beta_0+\beta_1 X_{1t}+\beta_2 X_2 t+\beta_3 \ln(t'+1)}$				Model 2: $\lambda_t = e^{\beta_0+\beta_1 X_{1t}+\beta_2 X_{2t}+\beta_3 \ln(t'+1)+\beta_4 (\ln(t'+1))^2}$				
	β_0	β_1	β_2	β_3	β_0	β_1	β_2	β_3	β_4
39 (38, 1)	-5.1130 (0.1586)	-0.0002 (0.0854)*	6.4452 (0.0757)*	-1.4830 (0.3143)	-5.1130 (0.1586)	-0.0002 (0.0854)*	6.4452 (0.0757)*	-1.4830 (0.3143)	-
40 (38, 2)	-5.0511 (0.1635)	-0.0002 (0.0852)*	6.3807 (0.0785)*	-1.0778 (0.1928)	-5.1130 (0.1586)	-0.0002 (0.0854)*	6.4452 (0.0757)*	-2.5175 (0.5521)	1.4924 (0.7233)
41 (38, 3)	-4.9833 (0.1691)	-0.0002 (0.0864)*	6.3079 (0.0819)*	-0.8558 (0.1454)	-5.1072 (0.1590)	-0.0002 (0.0852)*	6.4394 (0.0759)*	-2.2301 (0.4098)	1.1715 (0.5932)
42 (38, 4)	-5.1248 (0.1563)	-0.0002 (0.0891)*	6.4520 (0.0744)*	-1.0995 (0.0485)**	-5.0902 (0.1606)	-0.0002 (0.0890)*	6.4159 (0.0771)*	-0.8462 (0.6902)	-0.2007 (0.9024)
43 (38, 5)	-5.2662 (0.1441)	-0.0002 (0.0955)*	6.5900 (0.0676)*	-1.2696 (0.0171)**					
44 (38, 6)	-5.0283 (0.1627)	-0.0002 (0.0858)*	6.3539 (0.0779)*	-1.0050 (0.0136)**					
45 (38, 7)	-5.1169 (0.1550)	-0.0002 (0.0881)*	6.4433 (0.0734)*	-1.0944 (0.0059)**					
46 (38, 8)	-5.2436 (0.1439)	-0.0002 (0.0949)*	6.5649 (0.0674)*	-1.1780 (0.0023)**					
47 (38, 9)	-5.4680 (0.1267)	-0.0002 (0.0884)*	6.7995 (0.0576)*	-1.0441 (0.0011)**					
48 (38,10)	-5.6941 (0.1114)	-0.0002 (0.0619)*	7.0614 (0.0483)**	-0.8558 (0.0008)**					
49 (38,11)	-5.7694 (0.1062)	-0.0002 (0.0612)*	7.1380 (0.0455)**	-0.8255 (0.0005)**					
50 (38,12)	-5.9770 (0.0934)*	-0.0002 (0.0595)*	7.3483 (0.0390)**	-0.7351 (0.0006)**					
51 (38,13)	-6.5407 (0.0646)*	-0.0002 (0.0890)*	7.8719 (0.0260)**	-0.6283 (0.0014)**	-6.0279 (0.0874)*	-0.0002 (0.1255)	7.3327 (0.0375)**	-2.5031 (0.0122)**	0.8151 (0.0487)**
52 (38,14)	-6.6047 (0.0616)*	-0.0002 (0.0798)*	7.9423 (0.0244)**	-0.5558 (0.0027)**	-5.9866 (0.0891)*	-0.0002 (0.1239)	7.2918 (0.0384)**	-2.5953 (0.0052)**	0.8595 (0.0209)**
53 (38,15)	-6.6749 (0.0585)*	-0.0002 (0.0839)*	8.0054 (0.0231)**	-0.5299 (0.0032)**	-6.0114 (0.0879)*	-0.0002 (0.1170)	7.3229 (0.0376)**	-2.4577 (0.0041)**	0.7958 (0.0174)**
54 (38,16)	-6.6765 (0.0583)*	-0.0002 (0.0832)*	8.0054 (0.0230)**	-0.5087 (0.0037)**	-6.0938 (0.0834)*	-0.0002 (0.1171)	7.4069 (0.0353)**	-2.3077 (0.0035)**	0.7270 (0.0159)**
55 (38,17)	-6.6211 (0.0602)*	-0.0002 (0.0769)*	7.9541 (0.0238)**	-0.4925 (0.0040)**	-6.2599 (0.0744)*	-0.0002 (0.1267)	7.5662 (0.0310)**	-2.1498 (0.0033)**	0.6548 (0.0164)**
56 (38,18)	-6.6010 (0.0608)*	-0.0002 (0.0773)*	7.9307 (0.0241)**	-0.4754 (0.0045)**	-6.3068 (0.0723)*	-0.0002 (0.1227)	7.6173 (0.0299)**	-2.0489 (0.0029)**	0.6101 (0.0152)**
57 (38,19)	-6.4559 (0.0662)*	-0.0002 (0.0763)*	7.7749 (0.0267)**	-0.4164 (0.0105)**	-6.2319 (0.0754)*	-0.0002 (0.1256)	7.5384 (0.0314)**	-2.1740 (0.0010)**	0.6645 (0.0045)**
58 (38,20)	-6.4644 (0.0662)*	-0.0002 (0.0672)*	7.8011 (0.0264)**	-0.4436 (0.0063)**	-6.2818 (0.0736)*	-0.0002 (0.0933)*	7.6203 (0.0299)**	-1.8465 (0.0027)**	0.5258 (0.0149)**

** Significant at α =0.10; ** Significant at α =0.05.*

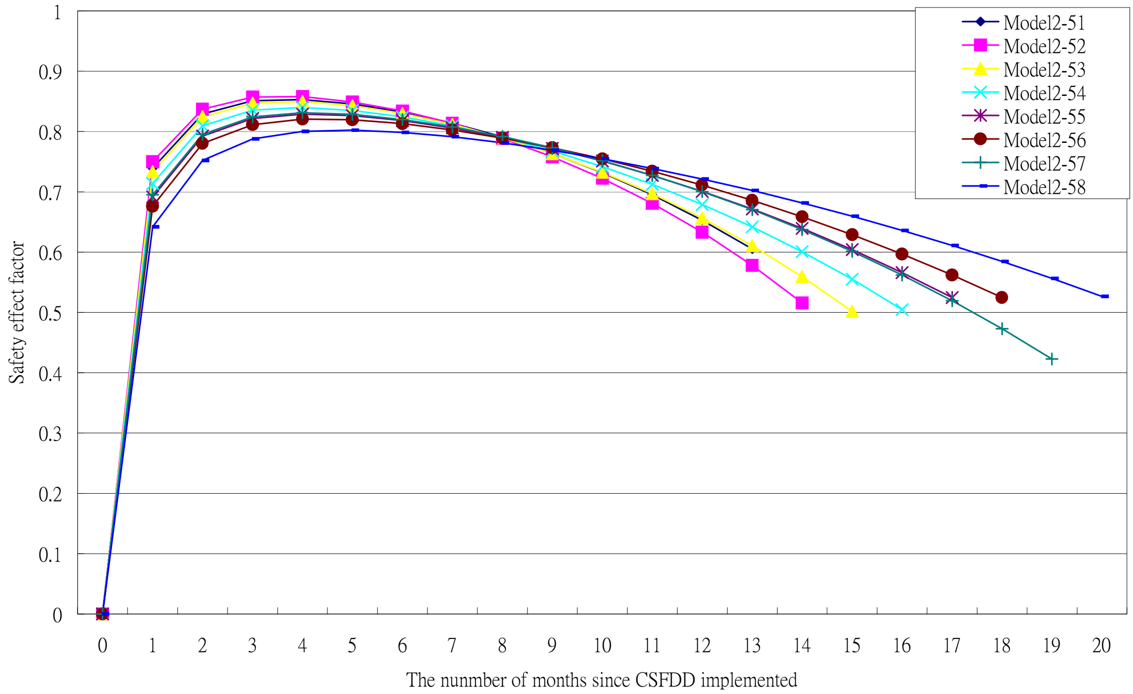

Figure 1. The Predicted Values of Safety Effect Factors of the CSFDD over Time for Model 2 with Different Lengths of Observation Periods (From 51-Month to 58-Month)

Although the time-based causal factor analysis method could measure the temporal variation of the policy effect quantitatively, the above results indicate that the choice of the length of observation periods may greatly affect the results. If analysts estimate the models with the shorter length of observation period, the results may show the effect of the policy has an increasing trend over time. However, the models estimated with the longer length of observation periods may find out that the effect presents as the initial increase followed with a period of decay.

6. DISCUSSION

The examples given here show that no matter which approaches we use, the estimated results of the same measure would be greatly influenced by using the different prior and post-implementation periods. According the results of the causal factor analysis with dummy-based specification, the length choice for prior implementation periods seems more important in measuring the effects of the other factors. Therefore, the longer length of the prior implementation periods might be beneficial in model estimation for controlling the effects of other factors.

The length choice for the post implementation periods seems to be more sensible than that for the prior implementation periods in measuring the safety effect of the CSFDD by pair-t tests. In addition, the results of the time-based causal factor analysis show that the different lengths of the post implementation periods may greatly affect the results. It indicates that while the results of the models with the shorter post-implementation period appear ineffective effects, those of the models with the longer post-implementation periods may obtain smaller sizes of the effect due to the decline of the policy effect. Though it is difficult to determine the appropriate length of post-implementation period, the longer post-implementation periods seem to be more appropriate than the shorter post-implementation period. In addition, it is important to alert analysts interpret their evaluation results estimated for using different observation periods carefully to avoid making an inappropriate conclusion.

Though the appropriate length of the observation period is not available, the above results suggest that analysts and authorities should monitor the policy effect from time to time rather than estimate the average effect of the policy during its implemented time period. Also, to monitor the changing process of the policy over the implementation period can assist the authorities to control the level of safety well. The Poisson regression models with time specifications could be used to formulate the effect of the target policy, and to estimate the models for every month (or other appropriate time interval) after implemented period. The two issues should be noted to apply the Poisson regression models with time specifications in measuring the temporal effects of the policy. First, the function forms might be different for the different policies. The choice of the function forms should depend on the potential changing pattern of the target policy over its evolution process. Second, the effects of the other factors should be controlled in order to measure the effect of the policy adequately.
Some implications have been derived from the results of the Poisson regression models with time specifications. When the estimated results show the effect of the policy presents increasing trend during observation periods, this may imply that the policy is still staying in the growth stage of its evolution process. Thus, the main task of authorities is to keep the effect of the policy increasing over time as long as they could. For example, the more resources and effort should be devoted into the promotion of the policy in order to increase the publicity of the policy, and then lead to deter the potential offenders. Thus, the effect of the policy may be keeping in the growing stage.

When the estimated results indicate that the increasing effect of the policy starts to decline, this may mean that the policy moves into the decline stage. This is an important opportunity for authorities to propose the enhancement, modification, or replacement of the inherent policy during this optimal timing. Why does the beginning of the decline stage be an optimal timing to introduce the new policy or modification of existing policy? Because the enhancement and modification of the inherent policy, or introduction of the new policy may need some time to take effect. Thus, the new policy or modification and enhancement of inherent policy may be able to take effect before the existing policy falls into the ineffective status.

When the authorities lose this opportunity, the target road safety problem may be out of control during the time period between the ineffective status of inherent policy and the beginning of the new policy effect. The accident costs induced during this time period are not necessary, while the authorities could adopt the appropriate actions at the right timing. Taiwan example has experienced this poor situation. Although the CSFDD policy has very dramatic effect on drunk driving accident reduction during its life cycle, the authority adopted new actions in the 59th month. The new policy has been taken effect after six months. If the authorities started the new intervention in the 12th month after the CSFDD implementing, the six-month promotion period will be ended in the 18th month after the CSFDD implementing. At least 8 months have been wasted for ignoring temporal variation of the policy effect. Thus, monitoring the changing pattern of the policy effect over its evolution process may save more lives and more accident costs.

7. **CONCLUSIONS**

The aim of this paper is simply to show that the different observation periods may greatly influence results. The main conclusions can be summarized in the following points:

1. Applying the pair-t tests to measure the effect of the CSFDD with different observation periods indicates that the choice of the lengths of the post-implementation periods will determine whether the effect of the CSFDD was significant, and the amount on reducing the number of alcohol-related fatal accidents. Furthermore, the length choice for the post implementation periods seems to be more sensible than that for the prior implementation periods in measuring the safety effect of the CSFDD.

2. Causal factor analysis techniques with the dummy specification are able to estimate the effect of road accident prevention policies with controlling other influencing factors. However, the similar problem arose from this analysis method in measuring the effect of the policy. If the different lengths of prior and post implementation periods are used to estimate the models, the results show the different size of effects for the models with different lengths of observation periods. It also shows that the length of the post implementation period is more sensible in measuring the effect of the CSFDD. In addition, the length of the prior observation period is more important in measuring the effects of the other factors.

3. Causal factor analysis techniques with time specifications demonstrate that how the choice of the lengths of the post implementation periods affects the estimated results of the policy effect. The results indicate that the models with the shorter post implementation periods may obtain the increasing pattern of the policy effect, but the models with the longer post implementation periods obtain the policy with the rapid initial response followed with a period of decay. The results suggest that the longer post implementation periods are more appropriate than the shorter post implementation periods in model estimation.

4. All approaches used to evaluate the effect of an intervention policy in this study indicate that the choice of the length of observation period will profoundly affect the results. It is, therefore, important to alert analysts interpret their evaluation results estimated by an observation period carefully to avoid making an inappropriate conclusion.

5. Though the appropriate length of observation period is not available, the study suggests that the continual monitoring of the policy effect over its evolution process is more important for analysts in evaluation of road safety measures as well as for authorities in management of road safety.

6. This study provided some demonstrations to show that the different observation periods may greatly influence results. However, the more different empirical examples should be examined to explore more insights in the future studies.

7. Fatal accidents, rather than all accidents, were used as an empirical example in this study. It is an interesting topic in considering the number of all accidents in the future study to explore deeply insights. Many interesting issues will be derived from considering the all crashes. First, the number of all crashes may not follow Poisson distribution. Second, the combination of different types of crashes is another issue.

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