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The life cycle of the policy for preventing road accidents: an empirical example of the policy for reducing drunk driving crashes in Taipei

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Abstract

The purpose of this paper is to examine the temporal variation of the effect of preventive policy on reducing traffic accidents. The life cycle theory was introduced to describe the safety effect of the intervening policy over time. Poisson regression models with dummy-based and time-based specifications were used to evaluate the effect of an intervening policy over an observation period following its implementation. The policy of "Criminal sanction for drunk driving (CSFDD)" in Taipei city was evaluated as an empirical example to determine whether the temporal variation of safety effect happened to the CSFDD policy. The study results showed that alcohol consumption, arresting the drunk driving offenders, and the implementation of the CSFDD were the significant factors affecting the rate of occurrence of fatal accidents involving drunk driving. The effect of the CSFDD policy appeared to be a rapid initial response followed by a lower rate of decay. The existence of the life cycle implies that employing different observation periods following the implementation of a specific policy to evaluate its performance may obtain different effects. The results of this study are crucial for policy evaluation. The effects of safety policy should be carefully interpreted in order to avoid misleading the relevant authorities in coming to the wrong conclusions and as such make the wrong decisions.

Keywords: Drunk driving; Life cycle theory; Poisson regression models

1. Introduction

Many intervention policies have been developed and implemented all over the world during the past two decades in order to reduce the number of traffic accidents. At the same time, a lot of observational before-and-after studies have been conducted to try and measure their effects on reducing the accident rate. Basically, the safety effect of an intervention policy either comes out quickly following its implementation (e.g. pavement resurfacing), or appears gradually (e.g. safety education). In addition, once the safety effect appears, it may increase with time over some period to reach its maximum, and then sustain this maximum effect indefinitely or decline gradually. The effect of safety measures 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. Thus, the temporal variation of the safety effect implies that each intervention policy may have its own unique evolution process within a different context. This means that researchers will face the problem of deciding when it is the appropriate time to measure the safety effect of a prevention policy after its implementation.

The conventional methods employed to measure the effect of an intervention policy regarding accident reduction can be classified into three categories. They are: pair *t*-test, time series analysis, and causal factor analysis (Hauer, 1997; Lacey and Jones, 2000; Chang and Yeh, 2003). 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. Two problems are noted when using the pair *t*-test to measure the safety effect. 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?

Time series analysis is another commonly used evaluation approach for measuring the safety effect of an intervention policy. Through model estimation and prediction, time series analysis can explore the trend of accident occurrences over time, and help the analysts to determine whether the intervention policy was effective in reducing the rate of

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traffic accidents. However, time series analysis is argued by its inherent drawback that it cannot discern the specific effects of individual factors affecting the accident occurrence. Although, this drawback could be somewhat improved by applying a multivariate time series model instead of a univariate time series model, nevertheless, the complicated technical requirements for modeling and computing often discourage the analysts from trying to do so. Furthermore, time series analysis involves a considerable amount of "data mining" and needs more observational data in evaluating the safety effect (Roger and Schoenig, 1994; DeYoung, 2000; Rehn and Gerhard, 2001). The end-result is that the evaluation work is unable to be conducted within a short period after the implementation of the intervention policy.

Causal factor analysis is the most popular tool for evaluating the safety effect of policy intervention (Miaou, 1994; Dionne et al., 1995; Agresti, 1996; Sohn, 1999; Li et al., 2001; Chang and Yeh, 2003). 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 (Miaou, 1994; Chang and Yeh, 2003). 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.

Neglecting the time variable of the safety effect may cause the effect of the policy to be misunderstood by researchers, and lead the relevant authorities to make poor decisions concerning the status, enhancement or replacement, of the existing policy. The temporal safety effect problem was mentioned by Hauer (1997); however, little attention has been paid on measuring its effect quantitatively in past literature. This study was undertaken to explore the factors affecting the safety effect of an intervention policy, and to determine whether the time variability of the policy effect exists. The life cycle theory (Wells and Gubar, 1966; Robbins, 1990; Kotler, 1994) was applied to develop a conceptual framework of the changing safety effect pattern brought about by the intervention policy over time. A Poisson regression model was used to formulate the relationship between the monthly accident frequencies and the candidate affecting factors, as well as the time following the implementation of the intervention policy. The implementation of criminal sanctions for drunk driving (CSFDD) in Taipei city was then taken as an empirical example to determine whether the time variability of the safety effect really existed for the CSFDD.

Following this section, the life cycle theory will be introduced, and a conceptual framework for the temporal variation of the safety effect for the intervention policy will be established in Section 2. The considerations for model formulation are presented in Section 3. The CSFDD program for Taipei city is introduced and available data for model estimation are prepared in Section 4. Model specifications for both dummy-based and time-based Poisson regression models are presented in Section 5. Model estimations and interpretations for both dummy-based and time-based Poisson regression models are presented in Section 6. Finally, concluding remarks are made in Section 7.

2. A conceptual framework for the life cycle of safety policy

A life cycle refers to a growth pattern with predictable change over time. The life-cycle theory has received a great deal of attention in marketing and organization studies (Wells and Gubar, 1966; Robbins, 1990; Kotler, 1994). It is commonly used to describe and analyze the lifetimes and/or growth patterns for specific companies or of manufactured products. The lifetimes of study objects are typically divided into four stages, by the theory of life cycle, as shown in Fig. 1. They are: emergence or formation, growth, maturity, and decline. Different products will have different life cycle patterns, which may have significant differences between durations for the same stage.

If we assume the intervention policy on reducing traffic accidents to be a product introduced by the government, then the four stages of the life cycle theory can be applied to formulate the safety effect of the intervention policy over its lifetime. The safety effect of the policy intervention may change with the passage of time due to two reasons (Hauer, 1997). First, the intervention itself may undergo changes over time (e.g. a poor design of the education program, or the gradual decay of some engineered improvement). Second, people's adaptation and perception of the particular intervention may change over time. In addition, people need time to adapt to, or perceive what has been implemented.

People need time to get familiar with the new policy after it has been introduced, and so the safety effect usually does not appear at the emergence stage. The duration of the emergence stage varies from case to case, and depends on the characteristics of policy, target group, promotion, enforcement, as well as the political environment. Once people are aware of, and feel affected by the new policy, they will begin to change their behavior to fit the requirements of the policy. At this stage, called the growth stage, the safety effect will become increasingly apparent. The more the people obey the new policy, the more the safety effect will increase. However, the safety effect of any intervention policy cannot increase infinitely, and will eventually reach a plateau of maturity. The maturity stage of some policies, like traffic safety education, might be expected to be sustained indefinitely. However, theoretically, most safety policies are recognized to decline after some substantial period at the maturity stage, due to various internal or external influences. As mentioned earlier, the duration of the four stages of a life cycle can vary significantly for different safety policies.

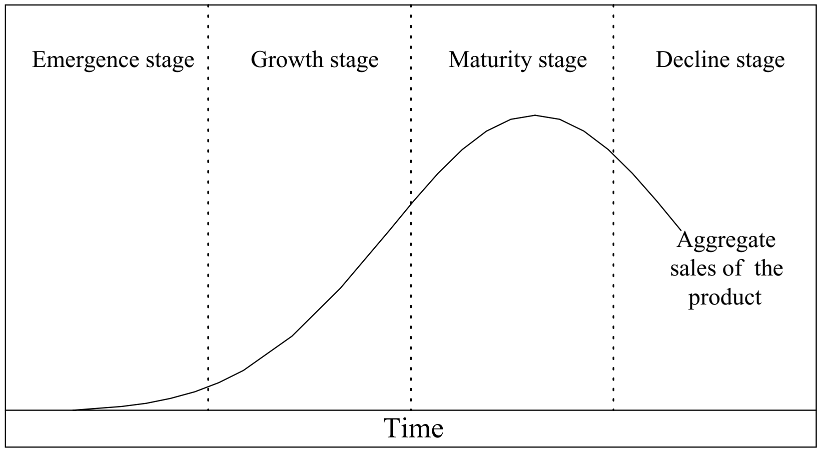

Fig. 1. The four stages of the life cycle theory.

Therefore, in practice, not all of the four stages of the life cycle of safety policies are necessarily found within limited observational periods. For example, the maturity stage of the safety education policy might not be found in 10 years of observation, however, the declining stages of some campaigns against drunk driving might be arrived at within 5 years.

Based on the above discussions, four possible safety effect patterns of the intervention policy will be found within an observational period *T* (see Fig. 2). For pattern A, the safety effect of the intervention policy did not appear within the observation period, and only the emergence stage was observed. In this case, the intervention policy is ineffective, or the observation period is not long enough to see the appearance of the policy effect. In pattern B, both the emergence and the growth stages of the safety effect are observed, and the safety effect of the intervention policy can be verified. However, the observers will fail to see the maximum effect the policy can achieve. The emergence, growth, and the maturity stages of the safety effect will be observed in pattern C, and the safety effect has reached its ultimate and sustained constant over some substantial period of time. And finally in safety effect pattern D, the entire life cycle of the intervention policy can be observed and the real safety effect over time can be properly identified.

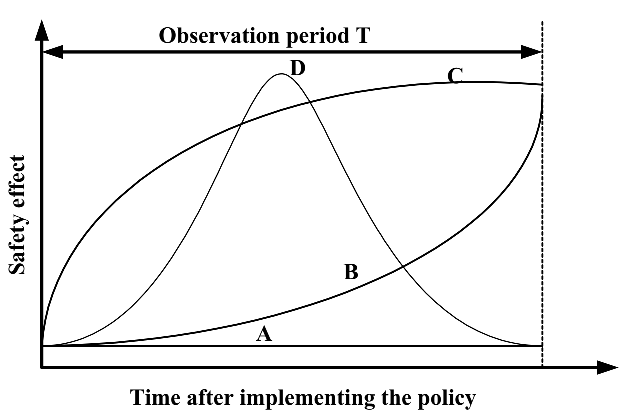

Fig. 2. Four possible safety effect patterns observed within an observation period *T*.

3. Considerations for model formulation

Enforcement is commonly thought of being an important factor that influences the effect of the intervention policy on accident reduction, especially the punishment related treatments. Therefore, the effect of an intervening policy on reducing traffic accidents over an observation period should be influenced by the level of enforcement. For example, the more enforcement is involved, the sooner the maturity stage will be reached. Furthermore, public attention is another important factor affecting the effect of the intervention policy (Roger and Schoenig, 1994; DeYoung, 2000). The promotion of a new policy through the mass media is powerful enough to increase the public's attention within a short period of time, and is expected to have a significant effect on accident reduction.

In order to clarify those effects corresponding to the life cycle of a specific policy, the model employed is supposed to have the capability of differentiating the safety effect of the life cycle from those brought about by other factors. Based on this requirement, the causal factor analysis models are preferred to pair *t*-test models as well as time series models, in order to explore the safety effect over time for a specific policy.

Selecting an appropriate observation interval is another important issue for model formulation. In order to collect enough samples for model estimation, the longer the observation interval is, the longer after implementation the evaluation work can be done. Furthermore, if the observation intervals are too long, the whole life cycle of an intervention policy could possibly occur in one interval, and one would fail to see the temporal variation of the policy effect over time. On the other hand, if the observation intervals are too short, some important information might not be available in the official statistics (e.g. daily enforcement data). Therefore, for the above reasons, monthly observational data are suggested for policy evaluation purposes.

Once the length of the observation interval has been decided, two types of models are available for model formulation. If the number of accidents that occurred in each observation interval is large enough, the linear (or nonlinear) regression models with least squares estimation method could be considered for the sake of convenience. The linear (or nonlinear) regression model is formulated as follows:

$$y_t = \beta_0 + \beta_1 x_t + f(\beta_2, t') + \varepsilon_t, \quad t = 1, \ldots, T \tag{1}$$

where y_t is the frequency of accidents that occurred in the observation interval t, x_t is a vector of contributing variables in interval t, t' is the number of observation intervals since the policy was implemented, $\beta_i{}'s$ are the vectors of parameters to be estimated, and ε_t is the error term. The values of t' are zero for the intervals before the policy was started, and a function of t', $f(\beta_2, t')$, is used to catch the temporal variation of the policy effect over the time after the implementation of the policy.

When the number of accidents that occurred in each observation interval is small, then the Poisson regression models, through the maximum likelihood estimation approach, could be considered for statistical robustness. The Poisson distribution is known to describe well the random behavior of the occurrence of discrete events such as accident frequency (Agresti, 1996; Hauer, 1997; Fridstørm et al., 1995; Sohn, 1999; Li et al., 2001; Shope et al., 2001; Chang and Yeh, 2003). 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.

$$P(y_t) = \mathrm{e}^{-\lambda_t} \frac{\lambda_t^{y_t}}{y_t!}, \quad t = 1, \ldots, T \tag{2}$$

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:

$$\lambda_t = \mathrm{e}^{\beta_0 + \beta_1 x_t + f(\beta_2, t')} \tag{3}$$

where x_t is the vector of contributing variables in the observation interval t, t' is the number of observation intervals since the policy was implemented, $\beta_i{}'s$ are the vectors of parameters to be estimated. The values of t' are zero for the intervals before the policy was started, and a function of t', $f(\beta_2, t')$, is used to catch the temporal variation of the policy effect over time after the policy was implemented.

4. Criminal sanction for drunk driving in Taipei city

In order to prepare for joining the World Trade Organization (WTO) as a member, the Taiwanese Government introduced further deregulations of alcohol-related products and industry during the past decade. The restrictions on alcohol-related products and industry have been reduced during the study period. For example, the advertising of alcohol-related products in the mass media, including television, has been permitted since 1996. As a result, the aggressive marketing of alcohol-related products has begun to encourage people to consume more alcohol. At the same time, the prices of alcohol-related products gradually lowered due to strong competition and the reduction of the import tax. This also has encouraged people to consume more alcohol. Therefore, drunk driving has become a severe social safety problem, and is a major concern for the Taiwanese public. A lot of effort has been devoted to deter people from driving while impaired during the past 10 years. The regulations in Taiwan stipulate that drivers with a breath alcohol content higher than 0.25 mg/l will be punished by a fine of NT$ 6000 (approximate US$ 180), suspension of their driver licenses for 6 months, and the mandatory attending of a four-hour education course. Drunk drivers who are found guilty in a fatal traffic accident will be deprived of their rights to drive a vehicle for the rest of their lives. However, this severe punishment still cannot stop people from driving while intoxicated.

At the end of 1998, two fatal accidents caused by drunk drivers attracted the public's attention and started some heated debates against drunk driving. Those events finally brought additional interventions to deter people from drunk driving, and the law of CSFDD was passed in May 1999. Under the new regulation, drivers with a breath alcohol content higher than 0.55 mg/l will be fined up to NT$ 60,000 (approximate US$ 1800), put into prison (for a maximum of 1 year), and have their driver licenses suspended for up to 3 years. These new rules for drunk driving were widely broadcast by television channels, radio stations, published on the Internet as well as in newspapers before they were implemented. It started another series of nationwide hot debates among the public.

Though the CSFDD policy was enacted to punish the drunk drivers with breath alcohol contents higher than 0.55 mg/l, it also deters potential offenders from driving while intoxicated, even with breath alcohol contents under 0.55 mg/l. Therefore, the CSFDD is expected to reduce the numbers of fatal accidents involving drunk drivers not only with a breath alcohol content higher than 0.55 mg/l but also with a breath alcohol content between 0.25 and 0.55 mg/l.

Thus, the drunk driving fatalities used in this study are the accidents that involved drivers who were found guilty to the accidents, and had a breath alcohol content higher than 0.25 mg/l. Fifty-eight monthly statistics for fatal traffic accidents involving drunk driving in Taipei city, from March 1996 to December 2000, were collected for model estimation. 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 was implemented as of the 39th observation month.

5. Model specifications

The number of monthly fatal drunk driving accidents that occurred in Taipei city ranged from zero to seven. Therefore, the Poisson regression models are preferred over the linear regression models in this study for formulating the accident occurrence involving drunk driving. Also, two kinds of model specifications are considered in this study in order to compare the temporal effect with the constant effect for an introduced policy. The first one is to treat the effect of CSFDD by a dummy variable, in which the average safety effect over an observation period is measured. We call models with this kind of specification: dummy-based specification models. The second one is the time-based specification model in which the effect of CSFDD is formulated by various functional forms of time having elapsed since its implementation.

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 the traffic accidents involving drunk driving. 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 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 the fatal accidents that involved drunk driving.

Taiwan had been working towards the World Trade Organization (WTO) for several years when the CSFDD policy was started being implemented. Consequently, several regulations on alcohol-related products and industry were lifted one by one over time in the periods before and following the implementation of the CSFDD. The decrease of the import tax on liquor, beer and wine dramatically reduced the prices of alcoholic drinks, and significantly influenced the alcohol consumption of people in Taiwan. It has been demonstrated that the more alcohol a society consumes, the more drunk driving accidents will occur (Deshapriya and Iwase, 1996; Voas et al., 2000). Therefore, including the variable of alcohol-consumption into the models is expected to avoid the potential bias in model estimations.

Measuring the alcohol consumption for a specific city in a given time interval is difficult in practice, and therefore the sales of alcohol or alcoholic beverages are usually used as a surrogate measure. However, only the yearly data for beer, wine and liquor sales of Taipei city are available. This forces us to include the yearly alcohol sales index into the model instead of the monthly alcohol sales index. We set the amount of sales of alcoholic beverages in Taipei city in 1996 as the alcohol sales index of one for the purpose of comparison. The values of the alcohol sales index for other years are then defined as a ratio of the amount of alcohol sales in a given year to the amount of alcohol sales in 1996. The yearly alcohol sales and the corresponding yearly alcohol sales index for Taipei city are summarized in Table 1. The variable of yearly alcohol sales index, X_{2t}, is served as a year-based covariate only, remaining constant over each month during the same year.

5.1. Dummy-based specification of the Poisson regression model

In the dummy-based specification model, we apply the dummy variable, X_{3t}, to represent the CSFDD policy being implemented in the tth month. The dummy-based Poisson regression model can then be formulated as Eq. (4). The dummy-based model can help us to catch the average safety effect of the CSFDD policy over the entire observation period. However, we fail to see the temporal variation of the safety effect over time brought about by the intervention policy in this type of model.

$$\lambda_t = \mathrm{e}^{(\beta_0+\beta_1 X_{1t}+\beta_2 X_{2t}+\beta_3 X_{3t})} \tag{4}$$

An additional variable is then further considered in order to test whether the series correlation exists when using the time series accident data for model formulation. That is to say, the number of fatal accidents involving drunk driving

Table 1
The yearly quantity of alcohol sales and the yearly alcohol sales index in Taipei

Year	Yearly quantity of alcohol sales in Taipei (liters)	The yearly alcohol sales index (1996 = 1)
1996	72532700	1.00
1997	67258200	0.93
1998	69223200	0.95
1999	74136600	1.03
2000	78814500	1.09

that occurred in the previous month, $y_{t-1,}$ is added to Eq. (4) to test the existence of series correlation as follows:

$$\lambda_t = e^{(\beta_0+\beta_1 X_{1t}+\beta_2 X_{2t}+\beta_3 X_{3t}+\beta_4 y_{t-1})} \quad (5)$$

5.2. Time-based specification of the Poisson regression model

In the time-based specification of the Poisson regression model, the most important issue is to find an appropriate functional form of $f(\beta, t')$ so as to catch the possible temporal variation patterns of the effect of the intervention policy. Basically, the function of $f(\beta, t')$ is supposed to have the capability to catch all the emergency, growth, maturity, and decline stages of the policy effect over time, based on the theory of the life cycle. The quadratic function of time t' is first considered as the candidate function of $f(\beta, t')$because of its simplicity. Hence, the expected number of fatal accidents involving drunk driving in the tth month is formulated as Eq. (6). Similarly, if we add the fatal accidents that occurred in the previous month to Eq. (6), then we will get Eq. (7) to test the existence of series correlation.

$$\lambda_t = e^{(\beta_0+\beta_1 X_{1t}+\beta_2 X_{2t}+\beta_3 t'+\beta_4 t'^2)} \quad (6)$$

$$\lambda_t = e^{(\beta_0+\beta_1 X_{1t}+\beta_2 X_{2t}+\beta_3 t'+\beta_4 t'^2+\beta_5 y_{t-1})} \quad (7)$$

The quadratic function of t' has an intrinsic drawback when applied to the formulation of the temporal variation of the safety effect of the intervention policy. That is to say, the quadratic function is a symmetric function, and will force the rates of growth and decline corresponding to the policy effect, to be equal. However, the CSFDD policy was introduced with major penalties and considerable public attention. The changing pattern of the CSFDD policy is expected as a rapid initial response followed by a period of decay. This implies that the CSFDD policy may have a very short emergence stage, move rapidly into a very steep growth stage, and is then followed by decay at a slower rate. Thus, some modification to the quadratic functional form is considered in order to provide the opportunity to catch the decay with a slower rate. That is, the natural logarithm transformation of time since the CSFDD was started, $\ln(t+1')$, is applied to replace the t' in Eqs. (6) and (7) and generate the following two new alternative models with Eqs. (8) and (9).

$$\lambda_t = e^{(\beta_0+\beta_1 X_{1t}+\beta_2 X_{2t}+\beta_3 \ln(t'+1)+\beta_4 (\ln(t'+1))^2)} \quad (8)$$

$$\lambda_t = e^{(\beta_0+\beta_1 X_{1t}+\beta_2 X_{2t}+\beta_3 \ln(t'+1)+\beta_4 (\ln(t'+1))^2+\beta_5 y_{t-1})} \quad (9)$$

6. Model estimation results and interpretations

6.1. Dummy-based specification models

Three dummy-based specification models were estimated in this study, differing only with respect to the set of explanatory variables used. An overview of these estimated models is shown in Table 2. Model D1 is the full model containing the constant term with all candidate explanatory variables. The results show that the coefficients of X_{1t} and X_{3t} are both negative as expected, and are significantly different from zero in Model D1. It implies that arresting drunk driving offenders, and implementing the CSFDD policy are shown to have significant effects on reducing fatal drunk driving accidents in the full model.

As expected, the yearly alcohol sales index variable, X_{2t}, is found to have a significant effect on the occurrence of alcohol-related fatal accidents in Model D1. It means the more the alcohol is consumed, the more the fatal accidents involving drunk driving will occur. However, the estimated results show that the parameter of y_{t-1} is not significantly different from zero. This means that the expected number of fatal accidents involving drunk driving in the tth month was not significantly affected by that of its previous month (y_{t-1}). Thus, we exclude the variable y_{t-1} from Model D1 to obtain Model D2.

The estimated results of Model D2 show that both the parameters of variables X_{2t} and X_{3t} are significantly different from zero. However, the estimated parameter of the variable X_{1t} is not significantly different from zero, even at $\alpha = 0.10$ in Model D2. The insignificant effect of X_{1t} in Model D2 might be the case that the number of drunk driving offenders arrested in the tth month was somewhat correlated with the fatal accidents involving drunk driving that occurred in the previous month y_{t-1}.

Table 2
The estimated results for the dummy-based specifications of Poisson regression models

Variables	Coefficients estimated for corresponding variables (*P*-values in parentheses)		
	Model D1	Model D2	Model D3
Constant	−7.6422 (0.0217)**	−7.5530 (0.0198)**	−9.7449 (0.0007)**
The number of drunk driving offenders arrested in the tth month, X_{1t}	−0.0002 (0.0859)*	−0.0002 (0.1157)	
The yearly alcohol sales index in tth month, X_{2t}	9.0840 (0.0073)**	8.8975 (0.0058)**	10.7705 (0.0003)**
The CSFDD was implemented or not in the tth month, X_{3t}	−1.3475 (0.0010)**	−1.2956 (0.0005)**	−1.4205 (0.0001)**
Fatal drunk driving accidents occurring in the $(t-1)$th month, y_{t-1}	−0.0067 (0.9224)		
Log-likelihood value	−32.1003	−33.1423	−34.3931

* Significant at $\alpha = 0.10$.
** Significant at $\alpha = 0.05$.

If we further remove the variable X_{1t} from Model D2, then we can obtain Model D3. The estimated results of Model D3 show that both the variables X_{2t} and X_{3t} have significant effects on the occurrence of alcohol-related fatal accidents. While the implementation of the CSFDD policy appeared to have significant effect on reducing number of fatal accidents involving drunk driving, nevertheless, the increase in alcohol consumption will cause the opposite effect on accident reduction during the observational period. Neither Model D2 nor Model D1 has significantly better explanatory ability than Model D3. Therefore, Model D3 seems to be the best one among the three dummy-based specification models in term of their statistical explanatory abilities. However, the devotion to enforcement, as represented by the number of arrested drunk driving offenders, X_{1t}, has a marginally significant effect ($P = 0.1157$) on reducing the fatal accidents involving drunk driving in Model D2. For prediction purposes, if only the dummy-based specification models are available, we would choose Model D2 over Model D3.

6.2. Time-based specification models

Four time-based specification models were estimated in this study, and their estimated results are summarized in Table 3. The estimated result of Model T1 shows that the coefficients of X_{1t}, t' and t'^2 are all significantly different from zero at $\alpha = 0.05$. The coefficient of X_{2t} is positive as expected, and is significantly different from zero at $\alpha = 0.10$. But, the variable y_{t-1} doesn't appear to significantly effect upon the occurrence of fatal accidents involving drunk driving in the tth month. This implies that the variable y_t is not significantly affected by series correlation.

Thus, we excluded the variable y_{t-1} from Model T1 and obtain Model T2. The estimated results of Model T2 show that the coefficients of X_{1t}, t' and t'^2 are all significantly different from zero at $\alpha = 0.05$. The variable of the alcohol sales index, X_{2t}, is found to have a significant effect on the occurrence of alcohol-related fatal accidents. Deleting the variable y_{t-1} from Model T1 does not significantly reduce its explanatory ability. Thus, Model T2 is thought to be better than Model T1 in this study.

The coefficients of Model T3 are all significantly different from zero, except the variable y_{t-1}. This again indicates that the variable y_t is not affected by series correlation. Similarly, excluding the variable y_{t-1} from Model T3 makes us obtain a better Model T4. The estimated results show that all the coefficients of Model T4 are significantly different from zero, and their signs are as expected. For this reason, Model T4 is thought to be better than the Model T3 in this study.

Model T4 has the same number of parameters to be estimated as Model T2 has, but Model T4 has a much higher log-likelihood value than Model T2. This verifies the expectation that Model T4 could catch the temporal variation of the safety effect of CSFDD policy better than Model T2. Furthermore, both the actual values and predicted values of the alcohol-related fatal accidents are plotted and shown in Fig. 3. The graph indicates that the residuals of Model T4 seem to be smaller than those of Model T2. Hence, Model T4 is chosen as the best one among the four time-based specification models estimated in this study.

6.3. Comparisons between dummy-based and time-based specification models

According to the model estimation results, Model D2 and Model T4 are the preferred models for dummy-based and time-based specification models respectively. The number of drunk driving offenders arrested, which was used as a

Table 3
The estimated results for the time-based specifications of Poisson regression models

Variables	Coefficients estimated for corresponding variables (*P*-values in parentheses)			
	Model T1	Model T2	Model T3	Model T4
Constant	−5.1633 (0.0003)**	−5.1036 (0.1470)	−6.6616 (0.0616)*	−6.2818 (0.0736)*
The number of drunk driving offenders arrested in the tth month, X_{1t}	−0.0003 (0.0388)**	−0.0002 (0.0421)**	−0.0002 (0.0611)*	−0.0002 (0.0933)*
The yearly alcohol sales index in tth month, X_{2t}	6.5594 (0.0721)*	6.4780 (0.0664)*	8.1702 (0.0245)**	7.6203 (0.0299)**
The number of months since the CSFDD was started, t'	−0.2437 (0.0108)**	−0.2311 (0.0049)**		
The number of months since the CSFDD was started, t'^2	0.0106 (0.0204)**	0.0105 (0.0107)**		
The number of months since the CSFDD was started, $\ln(t'+1)$			−1.9649 (0.0032)**	−1.8465 (0.0027)**
The number of months since the CSFDD was started, $(\ln(t'+1))^2$			0.5553 (0.0151)**	0.5258 (0.0149)**
Fatal drunk driving accidents occurring in the $(t-1)$th month, y_{t-1}	0.0065 (0.9265)		−0.0270 (0.7060)	
Log-likelihood value	−34.0923	−35.0939	−31.1359	−32.2255

* Significant at $\alpha = 0.10$.
** Significant at $\alpha = 0.05$.

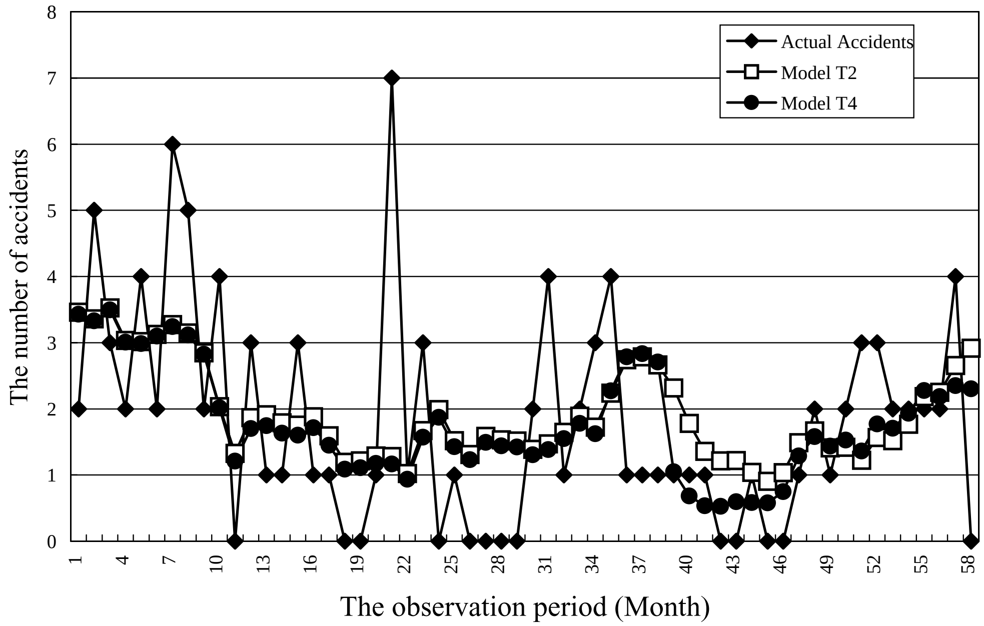

Fig. 3. The actual values and predicted values of the alcohol-related fatal accidents for Models T2 and T4.

proxy variable to reflect the compound effect of policy enforcement as well as the intervening policies that already existed, was a significant factor affecting the occurrence of fatal drunk driving accidents in Model T4, but they were only marginally significant in Model D2. Furthermore, the negative values (−0.0002) for the coefficients of X_{1t} in both Model T4 and Model D2, imply that the higher the level of police enforcement, the more the fatal accidents involving drunk driving will be reduced. It also indicates that if the police would arrest one hundred drunk driving offenders every month, the expected fatal accidents involving drunk driving in Taipei city will be reduced by 2% (i.e. $e^{-0.0002\times 100} = 0.980$). And, an 18% reduction of fatal accidents involving drunk driving will be achieved, if one thousand drunk drivers are arrested every month in Taipei city.

The use of alcohol was the second most significant factor affecting the occurrence of fatal drunk driving accidents in both Model D2 and Model T4. The positive values for the coefficients of yearly alcohol sales index in Model D2 and Model T4 (8.1701 and 7.6203, respectively) confirm that the more alcohol was sold to people, the more fatal accidents involving drunk driving will occur. According to the estimated results of Model T4, if an extra one million liters of alcohol were sold to the people of Taipei city in 1996, then the expected fatal accidents involving drunk driving in Taipei city would be increased by 11.1% (i.e. $e^{7.6203\times 0.014} = 1.111$) every month in that year.

The implementation of the CSFDD policy was the third significant factor affecting the occurrence of fatal drunk driving accidents in both Model D2 and Model T4. Although, Model D2 and Model T4 were not significantly different from each other in terms of their log-likelihood values, Model T4 offered the opportunity to see the temporal variation of the safety effect of CSFDD over time, rather than the average effect provided by Model D2. For comparing the changing patterns of the effects of the CSFDD policy of different models, the safety effects of the CSFDD policy for Model D2, Model T2, and Model T4 can be measured by the multipliers of $(1 - e^{\beta_3 X_3 t})$, $(1 - e^{\beta_3 t' + \beta_4 t'^2})$, and $(1 - e^{\beta_3 \ln(t'+1) + \beta_4 (\ln(t'+1))^2})$, respectively. These multipliers are called safety effect factors. The values of safety effect factors over time t' for Model D2, Model T2, and Model T4 are plotted and shown in Fig. 4.

Fig. 4 shows that the safety effect factor for Model D2 kept constantly at the value of 0.726 over time. This implies that the implementation of the CSFDD policy would reduce the fatal drunk driving accidents constantly by 72.6% over time. According to the estimated results of Model T2, the safety effect factor of the CSFDD policy grew with time t until reaching its maximum value of 0.720 in the 11th month. It then started to decline at the same rate as it had increased. The safety effect factor was 0.344 when we stopped our observation in the 20th month.

The safety effect factor of Model T4 increased sharply since the implementation of the CSFDD policy, until it reached the maximum value of 0.802 in the 5th month. Then the safety effect factor started to decline, but at a slower rate. The values of the safety effect factor in the 10th, 15th, and 20th month are 0.754, 0.659, and 0.526, respectively for Model T4. Because the CSFDD policy was introduced with major penalties and considerable public attention, its safety effect pattern appeared to be a rapid initial response followed by a slow rate of decay. All the four stages of life cycle, emergence, growth, maturity, and decline, were observed within the 20 months following its implementation in this study.

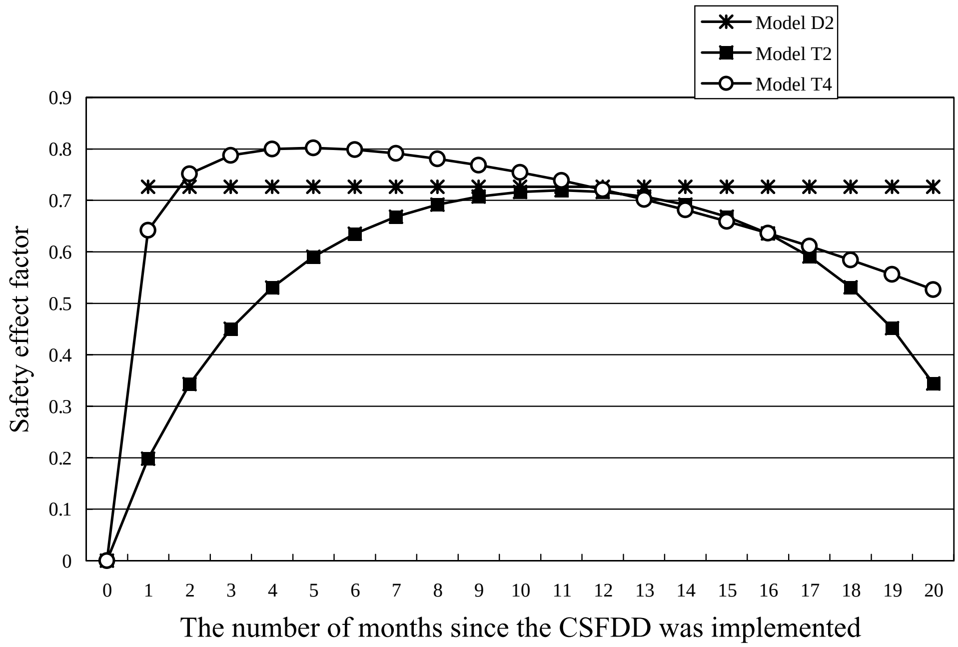

Fig. 4. The predicted values of the safety effect factor of the CSFDD over time for Models D2, T2, and T4.

7. Concluding remarks

The effect of the preventive policy on reducing the fatal accidents associated with drunk driving was estimated by controlling the level of enforcement as well as the use of alcohol in this study. The theory of life cycle was used to describe the effect of an intervening policy over time, and four possible safety effect patterns observed within an observation period were introduced. An evaluation of the effect of the CSFDD policy over time in Taipei city was conducted as an empirical example to demonstrate the existence of temporal variation for the effect of this preventive policy.

Poisson regression models with dummy-based and time-based specifications were developed to provide an insight into the occurrence of fatal drunk driving accidents. The estimated results of the preferred dummy-based specification model showed that both the use of alcohol and the implementation of the CSFDD policy had significant effects on reducing the occurrence of alcohol-related fatal accidents, but that the enforcement devotion had only a marginally significant effect. The study results showed that the CSFDD policy reduced the expected number of fatal drunk driving accidents on average by 72.6% over the 20 months following its implementation.

The results gained from the time-based specification models showed the quadratic function of natural logarithm transformation of time elapsed (i.e. $\ln(1 + t')$), could reasonably catch the safety effect pattern of the CSFDD policy over time. That is to say that the effect of the CSFDD policy appeared to be a rapid initial followed by a slow decay. The expected number of fatal drunk driving accidents was reduced by 64.2% in the 1st month following the implementation of the CSFDD policy, 75.2% in the 2nd month, and it obtained the maximum value of 80.2% in the 5th month. The safety effect factor started to decline with a slower rate over time starting at the 6th month, and reduced to 0.524 in the 20th month, when we ended our observation. As expected, both the number of drunk driving offenders arrested, and the yearly alcohol sales index appeared to have significant effects on the occurrence of fatal accidents involving drunk driving. All of the four stages introduced by the life cycle theory were observed in this empirical example, and the temporal variation for the safety effect of the CSFDD was verified in this study. It also indicated that different safety effects might be obtained if different approaches, or different observation periods following its implementation, are employed to evaluate the performance of an intervention policy. Hence, the results of safety effect evaluations for intervention policies should be interpreted carefully. An overly optimistic or pessimistic interpretation might lead the relevant authorities to make the wrong decision.

The time-based specification model was demonstrated to be better than the dummy-based specification model in evaluating the effect of safety policy on reducing the alcohol-related crashes in this study. Excluding the influences brought about by enforcement and alcohol consumption, the safety effect pattern over time for the CSFDD policy was explored in an observation period of 20 months following its implementation. This study found that there existed a temporal variation for the intervening policy. However, little attention has been paid on the mechanism that results in the temporal variation of safety effects for these intervening policies over their lives. It is suggested that more in-depth studies be conducted in the future on the factors affecting the temporal variation of intervening policies over their lives.

For lack of reliable and available information about the devotion of enforcement to the CSFDD policy, the number of drunk driving offenders arrested by police was used as a proxy variable to represent the enforcement devotion in this study. Some more appropriate data for the enforcement devotion should be considered in further studies. And, the information about the use of alcohol and the use of different types of alcoholic products, such as liquor versus beer versus wine consumption has met with similar problems as did the enforcement devotion. Furthermore, more functional forms (e.g. piecewise linear or nonlinear) about the safety effect patterns over time are suggested, in order to catch the possible evolution processes of the preventive policies. Finally, according to our results, the adoption of alcohol control policies may be a direction that is beneficial for reducing alcohol-related accidents.

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