Research Article

Evaluation of Section Speed Enforcement System Using Empirical Bayes Approach and Turning Point Analysis

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Speeding is a major risk factor for traffic-related injuries. As a countermeasure against speeding, automated speed enforcement systems (ASES) have been deployed in many countries. However, drivers’ awareness of enforcement locations allows themselves to adjust vehicle speeds in the vicinity of the enforcement locations. This enforcement avoidance behavior leads to a criticism of the effectiveness of ASES, in which the system promotes abrupt changes in vehicle speed near enforcement locations, increasing crash risk as a side effect.

Hence, the section speed enforcement system (SSES) was devised to induce this enforcement avoidance behavior over elongated distance (i.e., make drivers maintain lower speeds over the section to avoid the enforcement) and to induce synchronicity of speed across vehicles over the roadway section. SSES employs a pair of cameras that are mounted at two ends of a section. The system records each vehicle’s plate number and entry and exit times of the section and computes the vehicle’s average travel speed over the section (Figure 1). If the average travel speed exceeds the speed limit of the section, the corresponding vehicle is automatically fined. This system was first adopted in the late 1990s, and many countries have implemented the system under various

1. Introduction

Automated speed enforcement systems (ASES) have been introduced to mitigate speeding and are widely deployed in many countries. This type of enforcement system is installed to reduce traffic speed upstream of certain locations, especially where speeding-related crashes frequently occur. However, the local law often mandates informing drivers of enforcement locations, thereby drivers with that information naturally adjust their speeds to avoid enforcement: drivers tend to slow their speeds when approaching enforcement locations and return to their original speeds shortly after passing the locations [1–3]. This enforcement avoidance behavior leads to a criticism of the effectiveness of ASES, in which the system promotes abrupt changes in vehicle speed near enforcement locations, increasing crash risk as a side effect.

Hence, the section speed enforcement system (SSES) was devised to induce this enforcement avoidance behavior over elongated distance (i.e., make drivers maintain lower speeds over the section to avoid the enforcement) and to induce synchronicity of speed across vehicles over the roadway section. SSES employs a pair of cameras that are mounted at two ends of a section. The system records each vehicle’s plate number and entry and exit times of the section and computes the vehicle’s average travel speed over the section (Figure 1). If the average travel speed exceeds the speed limit of the section, the corresponding vehicle is automatically fined. This system was first adopted in the late 1990s, and many countries have implemented the system under various
names, including trajectory control in the Netherlands, average speed enforcement in the U.K., Tutor in Italy, point-to-point speed enforcement in Australia, and section control in the OECD [4].

Previous studies in various countries have reported that average speeds and crash occurrence diminished in roadway sections with SSES in operation [5–15]. Despite the consistency of outcomes across these studies, most of the studies were performed without comprehensive statistical analysis and, therefore, were unable to control for confounding factors and regression-to-the-mean [16]. Recently, some studies have employed the empirical Bayes (EB) approach to evaluate the safety benefits of SSES. Montella et al. [17] showed that total crashes after SSES installation diminished by 31.2%. Høye [2] performed meta-analysis based on outcomes across four different study sites and concluded with a summary effect of 20% reduction in crash occurrence. Using EB analysis, Høye [18] found 49% reduction in crashes with fatal and severe injuries after the installation of SSES. However, these studies did not investigate the specific effect of SSES on vehicle speed, the key antecedent for crash reduction as induced by SSES.

These studies evaluated crash occurrence using the EB method, which is widely used in controlling for confounding and regression-to-the-mean issues in the before-and-after study [19]. The EB method divides the entire period of evaluation into two separate time intervals, before and after the installation of the SSES. This is based on the assumption that the installation of SSES was the only intervention to reduce crash occurrence. However, if there were other unobserved factors, the inferences drawn from the EB could be invalid [20, 21]. Thus, it is necessary to evaluate the actual turning point in the trend of crash occurrence. An alternative method to validate or reinforce the causal inference from the EB method is turning point (TP) analysis, which can statistically identify changes in time-series data [22, 23].

In this context, we have collected vehicle speed and crash data from expressway sections where SSESs were in operation (Section 2). We examined speed profiles from loop detectors installed along three sections and compared outcomes with those from neighboring sections (Section 3). For all nine study sites, we performed EB and TP analyses to evaluate the effect of SSES on safety performance (Section 4). Finally, we explain the comprehensive effectiveness of SSES and discuss implications (Section 5).

2. Descriptions of Site and Data

2.1. Study Sites. In South Korea, ASES has since its inception in 1997 been deployed at more than 5,500 locations on roadways. In 2007, SSESs were first introduced on Korean expressways, and 48 SSESs were in operation over the network of Korean expressways as of 2018. Nine study sites, as listed in Table 1, were selected because SSESs were first installed at those sites such that sufficient observation of crash occurrence was possible.

2.2. Data for Speed Analysis. For cross-sectional speed analysis, three study sites out of nine were selected using the following criteria: (i) sites do not contain any attributes such as tunnels, bridges, or vertical and horizontal curves that may influence driving patterns compared to comparison sections and (ii) loop detector data were available. Only three study sites (ID 6, 8, and 9) were used for the speed analysis because we were unable to set up the comparison sections with the similar attributes and geometry in other six study sites. The selected sites comprise 36.6 lane-kilometers of 100 km/h zones and 28.2 lane-kilometers of 110 km/h zones. Loop detector data were obtained from all three study sites, while the SSESs were in effect.

2.3. Data for Safety Analysis. For the safety analysis, crash data and annual average daily traffic (AADT) were obtained...
| Site ID | Route name (section ID)                  | Direction | Postkilometer Start | Distance | Speed limit  | Attributes                        | Enforcement starting date | Analysis period* | AADT Before | AADT After | No. of crashes Before | No. of crashes After |
|---------|----------------------------------------|-----------|---------------------|----------|--------------|-----------------------------------|--------------------------|-------------------|--------------|-------------|----------------------|---------------------|
| 1       | Seohaean Expressway (I) NB (to Seoul)  | NB        | 273.5               | 9.1 km   | 110km/h      | Bridge, rest area                 | 01/15/2008              | B/A 12-month     | 91,712      | 98,222     | 11                    | 8                   |
| 2       | Seohaean Expressway (II) SB (to Mokpo) | SB        | 282.6               | 9.1 km   | 110km/h      | Bridge, rest area                 | 01/15/2008              | B/A 12-month     | 91,774      | 98,218     | 17                    | 17                  |
| 3       | Pyeongtaek-Jecheon Expressway WB (to Pyeongtaek) | WB | 11.2               | 5.5 km   | 100km/h      |                                    | 12/24/2008              | B/A 12-month     | 78,736      | 82,655     | 5                     | 5                   |
| 4       | Yeongdong Expressway (I) EB (to Kangnung) | EB | 168.5               | 7.5 km   | 100km/h      | Tunnel                            | 12/26/2007              | B/A 12-month     | 21,581      | 20,949     | 21                    | 11                  |
| 5       | Yeongdong Expressway (II) WB (to Incheon) | WB | 172.2               | 10.4 km  | 100km/h      | Tunnel                            | 10/16/2009              | B/A 33-month     | 58,263      | 59,429     | 54                    | 25                  |
| 6       | Jungbunaenuk Expressway (To Masan) | (To Masan) | 223.9               | 14.1 km  | 110km/h      | Tunnel                            | 12/20/2008              | B/A 24-month     | 19,031      | 19,612     | 16                    | 17                  |
| 7       | Jungang Expressway SB (to Busan) | SB        | 242.4               | 5.6 km   | 100km/h      | Tunnel                            | 02/21/2008              | B/A 12-month     | 33,894      | 33,828     | 3                     | 3                   |
| 8       | Daejeon-Tongyeong Expressway SB (to Tongyeong) | SB | 85.5                | 7.5 km   | 100km/h      | Tunnel                            | 01/01/2009              | B/A 24-month     | 39,592      | 42,402     | 26                    | 9                   |
| 9       | Yeongdong Expressway (III) EB (to Kangnung) | EB | 215.2               | 10.8 km  | 100km/h      |                                    | 12/07/2011              | B/A 24-month     | 81,230      | 84,885     | 19                    | 8                   |

* B/A 12-month means 12-month analysis period before-and-after installation (total 24 months).
for the periods before and after SSES installation. The number of crashes is used in the EB method and TPA; the AADT data were used to construct a prediction model for the safety performance function (SPF), which is input to the EB method. In the safety analysis, we analyzed crash data for all nine study sites. A longitudinal before-and-after analysis was conducted in the safety analysis. SSESs for all nine study sites went into effect prior to 2011, and, therefore, long-duration observation of crash occurrence was possible. The study period is set from 2007 to 2013 because there were changes in geometry of some of our study sites after 2014, which may have affected crash occurrence. Details on each study site are furnished in Table 1.

3. Speed Profile Analysis

3.1. Cross-Sectional Analysis with Comparison Sections. Two groups were used for the comparative analysis. One group is the enforcement sections shown in Table 1, and the other group is a comparison section where the site attributes are almost identical to the enforcement sections except for the existence of enforcement. The comparison sections are selected as upstream and downstream sections surrounding the enforcement section because the same groups of drivers traveling in those sections and geometric and local characteristics are similar. Figure 2 illustrates the layouts of the enforcement and comparison sections in all three selected study sites. The sections are two-lanes along their length except auxiliary lanes in the vicinity of merging and diverging areas. To this end, only traffic data that were collected from mainline areas (i.e., lanes 1 and 2) are used in this study. In the case of the Yeongdong Expressway (ID 9), only one comparison section was used, unlike other sites. This is because the enforcement section is at the end of the Yeongdong Expressway, and, therefore, the downstream section was too short to be used as a comparison section.

3.2. Data Filtering. To enhance the comparability and to unveil changes in driving patterns along the sections, the collected loop detector data were filtered to include data only from unconstrained, free-flow travel conditions when drivers could travel at their desired speeds, and thus over-speeding could occur. In Figure 3, the fundamental diagram illustrates a relation between traffic flow and density. Although scatter plots of flow vs. density data could form various shapes such as reverse lambda, parabolic, and triangular, the diagram in any shape exhibits two distinguished regimes–free-flow and congested. On the left-side branch, the traffic is in the free-flow regime where speed remains at free-flow without any constraint, and the right-side branch presents congested regime where the flow is constrained.

Figure 3 displays scatter plots of flow versus density at one of the detectors among the study sites. Firstly, abnormal loop detector data were filtered out by using daily statistics algorithm by Chen [24]. To ensure that the values were from traffic that was not constrained, we secondly filtered out the data from periods when vehicular interactions occurred and thus obscured overspeeding patterns: data points associated with densities lower than 10 vehicles/km/lane, which correspond to approximately half of the density at capacity, were used in the present study [25]. The analysis of speed profile is intended to inspect changes in vehicle speeds solely due to the installation of SSES. If the data contain traffic conditions that constrained vehicle speeds (i.e., congestion), it is hard to distinguish whether the speed changes, if any, was due to the changes in drivers’ speed-taking behavior that was induced by effect of SSES.

3.3. Effects of SSES on Vehicle Speed. To compare speed profiles between enforcement and comparison sections, descriptive summary statistics of each section were evaluated using a box-and-whisker plot (Figure 4). Bottom and top of box indicate first and third quartiles, respectively. Horizontal line in the middle of the box is the median. Top and bottom ends of the vertical line traversing the box are boundaries of data, excluding outliers. It is notable that boxes from the enforcement section are narrower and lower than those from the comparison sections. This means that vehicles traversed the enforcement section under more stable condition, as can be inferred from the lower mean and variance of speed in the enforcement section.

As shown in Figure 4, the three study sites showed the same speed analysis results that the average speed was lower than the speed limit throughout the enforcement section. One of the possible negative sides of SSES is the higher variance of speed at the beginning and the end of the enforcement section. Because SSES enforces vehicles by the average speed, there could be vehicles that move at high speeds in the beginning and lowered the speeds in the end or vice versa. However, this phenomenon was not observed in this study. T-test and F-test were performed to statistically validate the differences of mean and variance between enforcement and comparison sections. The test results confirm that the differences are statistically significant at 5% significance level, and the speed variance is reduced not only along the enforcement section but also across vehicles.

4. Safety Analysis

In this section, we evaluate the effect of installing SSES on traffic safety. The EB method is applied to compare changes in crash occurrence before and after SSES installation (Section 4.1). Then, a comprehensive inference was drawn by applying meta-analysis to the outcome of the EB method at each site (Section 4.2). To validate that, if they exist, changes in crash occurrence happened prior to and near the installation of SSES, we performed TPA to statistically identify turning points in time-series crash occurrences (Section 4.3) and to compare turning points with the installation of SSES (Section 4.4).

4.1. EB Method with Comparison Group. In this study, the EB method with a comparison group was adapted to compare the safety performance before and after installation of SSEs. Because it employs a crash prediction model, the EB method can adjust regression-to-the-mean (RTM) bias [19] and can
address changes in traffic volume. However, the effect of general changes (i.e., temporal trend) in traffic crashes from the before to after periods still exists. To adjust this issue, the comparison group method is combined for estimating the predicted number of crashes.

Generally, the treatment group is composed of the limited number of samples, and it can hardly incorporate the effect of temporal trend in crash occurrences. Meanwhile, the comparison group can affect the term, \( \bar{m}_i \), the predicted number of crashes that is estimated based on the information on the crash occurrences in the entire area as well as the SSES area. Hence, the EB method with the comparison group can account for the effect of temporal trend in crash occurrences in the area.
Figure 4: Speed distributions at loop detectors of three different study sites: (a) Jungbunaeruk Expressway (ID 6), (b) Daejeon–Tongyeong Expressway (ID 8), and (c) Yongdong Expressway (ID 9).
The effectiveness \( e_i \) is measured by comparing the numbers of crashes at a site \( i \) before and after the installation of SSES:

\[
e_i = \frac{x_i^n}{\hat{m}_i^b \cdot (C_i^n/C_i^b)}
\]

where \( x_i \) is the observed number of crash occurrences in the period after SSES went in effect and \( \hat{m}_i^b \) is the expected number of crashes that would have occurred in the same period if SSES had not been implemented. To consider the trend in crash occurrence that would have been expected regardless of SSES (i.e., changes that naturally occur), we adjusted \( \hat{m}_i^b \) by \( C_i^n/C_i^b \). The numerator, \( C_i^n \), is the observed number of crashes in the control group in the period after installing SSES, and \( C_i^b \) is the observed number of crashes in the control group in the period before installing SSES. All variables to compute \( e_i \) are observable, except for \( \hat{m}_i^b \).

\( \hat{m}_i^b \) is estimated as the weighted sum of the predicted number of crashes in the before-period \( (P_i^b) \) and the observed number of crashes in the before-period \( (x_i) \):

\[
\hat{m}_i^b = w^b \cdot P_i^b + (1 - w^b) \cdot x_i
\]

where the weight, \( w^b \), is derived based on estimated outcomes of the prediction model:

\[
w^b = \frac{1}{(1 + \alpha \cdot P_i^n)}
\]

In general, the prediction model is estimated using a negative binomial (NB) regression; the parameters in equation (3) are the estimated outcomes: \( \alpha \) is the over-dispersion parameter, and \( P_i^n \) is the expected number of crashes estimated from the prediction model. For the crash prediction model, we have used the crash data for four years (2007–2010) and the annual average daily traffic data from 1,128 roadway segments of Korean expressways. In this study, we adopted the prediction model that was previously specified for the same coverage of Korean expressways in Shim et al. [3]. The prediction model is crashes/year = \( l \times \exp(0.225 + 1.45 \times 10^{-3} \times \text{AADT}) \), where \( l \) is the length of the section and AADT is the average annual daily traffic for the section. The estimated over-dispersion parameter \( k \) is 0.183.

4.2. Results: EB Method and Meta-Analysis. The descriptive statistics of crash data are summarized in Table 2. Also, the results of the EB analysis are summarized in Table 3 and show that crash occurrence diminished at eight out of the nine study sites. However, the reductions were statistically significant only at three sites (ID 5, 8, and 9) due to lack of crash occurrence, and the outcomes were found to vary widely across sites. This phenomenon often arises because crash occurrences are by nature rare events, and, therefore, only a few crashes were observed during the observation period. For more comprehensive evaluation of the overall effect of SSES, we performed meta-analysis with the outcomes from all nine study sites. Meta-analysis is a statistical approach that combines outcomes from multiple study sites. This study adapted a fixed-effect meta-analysis by Fleiss et al. [26] that combines the effectiveness \( (E) \) across the sites by assigning the inverse of variance as a weight factor. As a result, an overall index of effectiveness \( (\hat{E}) \) and confidence interval were derived as follows:

\[
\hat{E} = \exp\left[\frac{\sum_{i=1}^{n} f_i \cdot \ln(e_i)}{\sum_{i=1}^{n} f_i}\right]
\]

95% C.I. = \( \exp\left[\frac{\sum_{i=1}^{n} f_i \cdot \ln(e_i)}{\sum_{i=1}^{n} f_i} \pm \frac{1.96}{\sqrt{\sum_{i=1}^{n} f_i}}\right] \)

where the weight factor \( f_i \) is estimated based on the variance of \( e_i \) and \( s_i^2 \) at each site.

\[
f_i = \frac{1}{s_i^2}, \quad \text{where } s_i^2 = \frac{1}{m_i^b} + \frac{1}{\hat{m}_i^b} + \frac{1}{C_i^n} + \frac{1}{C_i^b}
\]

As a result, \( \hat{E} \) is 0.57, meaning that the number of crashes decreased by 43% for all study sites. The confidence interval of \( \hat{E} \) ranges from 0.44 to 0.73—the upper level is well below one—implying that the overall effect of SSES reduces crash occurrences at 95% confidence level.

4.3. Turning Point Analysis. We employed statistical examination using TPA to determine whether turning points in crash occurrence were temporally consistent with the installation of SSESs [22]. TPA was performed based on the assumption that crash occurrences in \( n \) time intervals, \( \{x_i; i = 1, \ldots, m, \ldots, n\} \), during our observation period were from two different distributions before and after an unknown turning point at \( m (m < n) \). The Poisson distribution was naturally the choice because crash occurrences are rare and discrete events over time. However, over-dispersion (i.e., variance greater than the mean) often estimate plagues using the Poisson regression, which was also the case for our study.

This study generalized the application of TPA by using negative binomial (NB) distributions, which have two parameters in the probability mass function (PMF). Therefore, instead of computing Maximum a Posteriori, we used the Newton–Raphson method to search for the turning point, \( m \), where two NB distributions are most likely to be different from a statistical perspective.

The two NB distributions \( (P_0 \) and \( P_1 \) ) with a conjugate prior distribution as a beta distribution have shaper parameters \( (a_0, a_1) \) and rater parameters \( (b_0, b_1) \), and turning point \( m \) is equally likely over time. Thus, \( P_0 \sim \text{Beta}(a_0, b_0) \), \( P_1 \sim \text{Beta}(a_1, b_1) \), and \( m \sim \text{Uniform}(0, n) \). We set \( a_0 = a_1 = n_0 \) (mean of \( x_i \) ) and \( \beta_0 = \beta_1 = 1 \). The posterior function, \( f(m, P_0, P_1 \mid x_1, n) \), the likelihood function, \( L(x_1, n \mid m, P_0, P_1) \), and the prior function, \( f(m, P_0, P_1) \), are as follows:
\[
f(m, p_0, p_1 \mid x_i) \propto L(x_i, n \mid mp_0, p_1) \cdot f(m, p_0, p_1)
\]
\[
= L(m, p_0, p_1) \cdot f(m, p_0, p_1)
\]
\[
= \prod_{i=1}^{m} \left( x_i + r_0 - 1 \right) p_0^{x_i} (1 - p_0)^{r_0} \cdot \prod_{i=m+1}^{n} \left( x_i + r_1 - 1 \right) p_1^{x_i} (1 - p_1)^{r_1}.
\]

\[
\frac{\Gamma(a_0 + \beta_0)}{\Gamma(a_0) \cdot \Gamma(\beta_0)} p_0^{a_0 - 1} (1 - p_0)^{\beta_0 - 1} \cdot \frac{\Gamma(a_1 + \beta_1)}{\Gamma(a_1) \cdot \Gamma(\beta_1)} p_1^{a_1 - 1} (1 - p_1)^{\beta_1 - 1} \cdot \frac{1}{n}
\]
We have four unknown parameters $r_0$, $r_1$, $p_0$, and $p_1$. Starting from $m = 1$, we solve equations (8) and (9) using the Newton–Raphson method (for $r_0$ and $r_1$). Outcomes from these equations were then input to solve equations (10) and (11) (for $p_0$ and $p_1$). Using those four parameters, we updated $\ln(f)$. We iterate this procedure until $m = n$, and we search for $m$ that will maximize $\ln(f)$.

\[
\ln(f) = \sum_{i=1}^{m} \ln\left(\Gamma\left(x_i + r_0\right)\right) - \sum_{i=1}^{m} \ln\left(\Gamma\left(x_i + 1\right)\right) - m \cdot \ln\left(\Gamma\left(r_0\right)\right)
\]
\[
+ \sum_{i=m+1}^{n} \ln\left(\Gamma\left(x_i + r_1\right)\right) - \sum_{i=m+1}^{n} \ln\left(\Gamma\left(x_i + 1\right)\right) - (n-m) \cdot \ln\left(\Gamma\left(r_1\right)\right)
\]
\[
+ \left(\alpha_0 - 1 + \sum_{i=1}^{m} x_i\right) \cdot \ln(p_0) + (m \cdot r_0 + \beta_0 - 1) \cdot \ln(1 - p_0)
\]
\[
+ \left(\alpha_1 - 1 + \sum_{i=m+1}^{n} x_i\right) \cdot \ln(p_1) + ((n-m) \cdot r_1 + \beta_0 - 1) \cdot \ln(1 - p_1),
\]

\[
\frac{\partial \ln(f)}{\partial r_0} = \sum_{i=1}^{m} \varphi\left(x_i + r_0\right) - m\varphi\left(r_0\right) + m \cdot \ln(1 - p_0) = 0,
\]

\[
\frac{\partial \ln(f)}{\partial r_1} = \sum_{i=m+1}^{n} \varphi\left(x_i + r_1\right) - (n-m) \cdot \varphi\left(r_1\right) + (n-m) \cdot \ln(1 - p_1) = 0,
\]

\[
\frac{\partial \ln(f)}{\partial p_0} = \frac{\alpha_0 + \sum_{i=1}^{m} x_i - 1}{\alpha_0 + \beta_0 + \sum_{i=1}^{m} x_i + r_0 \cdot m - 2} = 0,
\]

\[
\frac{\partial \ln(f)}{\partial p_1} = \frac{\alpha_1 + \sum_{i=m+1}^{n} x_i - 1}{\alpha_1 + \beta_1 + \sum_{i=m+1}^{n} x_i + r_1 \cdot (n-m) - 2} = 0.
\]

### 4.4 Results: Turning Point Analysis

We have aggregated the outcomes from nine study sites to draw a more general inference about the temporal trend of crash occurrence as well as to compensate for the insufficient observation of crash occurrences. To this end, we counted crash occurrences in a quarter-year time interval and aggregated across sites with respect to the installation of SSESs. The $x$-axis in Figure 5 indicates the number of quarters relative to the time of SSES installation—the installation of SSESs is 0 and the month with SSES installed is not included in the analysis. Log-posteriori values are shown as a line along the primary $y$-axis, while the numbers of crashes are displayed as a bar graph along the secondary $y$-axis. Log-posteriori value continuously increases until 0 (i.e., installation of SSES) and gradually diminishes thereafter. Note how the maximum log-posteriori turning point temporally matches the installation of SSESs. This means that the most prominent statistical change in crash occurrence was observed after installation of SSES.

Figure 6 shows probability mass functions (PMF) of the two NB distributions—dividing the time period with respect to the turning point (i.e., before and after installation). The grey and black distributions are NB distributions before and after the turning point, respectively. The after-distribution is skewed to the left compared to the before-distribution, meaning that the probability of crash occurrence after the turning point is relatively low. In other words, the reduction in crash occurrence was statistically significant immediately after installation of SSES.

### 5. Conclusion

SSESs have been introduced to control speeding over roadway stretches and to remedy the enforcement avoidance behavior prevalent for ASES, including momentary slowing only at locations of enforcement [3]. In this study, based on data from nine Korean expressway sections where SSESs had been installed, we evaluate the effectiveness of SSES on reducing vehicle speed and crash occurrence. Speed distributions were constructed using vehicle speed data from loop detectors along the monitored expressway stretches. The distributions showed that both the mean and the variance of the speeds were lower inside the enforcement sections than in neighboring sections; especially, reductions in variances were pronounced. This implies that SSES can reduce vehicle speeds
as well as speed variation across enforcement sections and, consequently, lowers the risk of crash occurrence.

To validate this conjecture, we performed in-depth analysis of crash data. First, we divided our observations into two time periods—before and after—and compared crash occurrences between the two time periods using the EB method. The outcomes indicated that crash occurrence decreased in eight of the nine study sites, and an overall 43% reduction was estimated when we combined the outcomes across sites using meta-analysis. TPA outcomes supplemented these findings and ensured that reductions in crash occurrence corresponded temporally to (i.e., happened shortly after) the installation of SSESs.

There are limitations when interpreting the results of safety analysis at each individual site because the effectiveness index may be affected by unobserved factors that reside in particular study sites. This becomes more pronounced at the sites with small samples. To compensate for this phenomenon, we performed meta-analysis, which allowed the evaluation of the comprehensive effect of SSES on the crash occurrences.

The findings from these analyses of traffic speed and safety suggest that SSES can stabilize traffic flow (reduce mean and variance of speeds) where it is installed and thereby have a positive effect on traffic safety. We reached this conclusion because averages and variations of vehicle speed are proportional to risk of crash [27–33], though observations of traffic flow and safety were performed separately. This separate observation was inevitable because observation of traffic crashes, which are rare as statistical events, generally requires substantial time. Because this study is based purely on observations, it is difficult to draw causal relationship between traffic conditions and safety effects. Furthermore, the period of data collection was limited. Studies based on long-term observations still remain a challenge for future research.

The present study demonstrated that SSES could stabilize vehicle speed over long distances because drivers tend naturally to avoid enforcement and, therefore, comply with the speed limit over monitored sections. It is evident from these observations that, unlike ASES, there were no momentary and abrupt speed reductions along sections with SSES. Furthermore, the 43% reduction in crash occurrence in the sections with SSES is 5.6 times greater than the reduction with ASES, which showed only a 7.6% reduction, as reported in a previous study also performed with data from Korean expressways [3]. It is manifested that SSES has more favorable effects on traffic safety and constant vehicle speed than does conventional ASES.

Data Availability
The speed and safety data of Korean Expressway used to support the findings of this study were supplied by Korea Expressway Corporation (http://www.ex.co.kr/). Requests for access to these data should be made to the data portal of Korea Expressway Corporation (http://data.ex.co.kr/).

Conflicts of Interest
The authors declare that they have no conflicts of interest.

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References

[1] E. De Pauw, S. Daniels, T. Brijs, E. Hermans, and G. Wets, "Automated section speed control on motorways: an evaluation of the effect on driving speed," Accident Analysis & Prevention, vol. 73, pp. 313–322, 2014.

[2] A. Høye, "Speed cameras, section control, and kangaroo jumps—a meta-analysis," Accident Analysis and Prevention, vol. 73, pp. 200–208, 2014.

[3] J. Shim, S. H. Park, S. Chung, and K. Jang, "Enforcement avoidance behavior near automated speed enforcement areas in Korean expressways," Accident Analysis and Prevention, vol. 80, 2015.

[4] ETSC, "Section control: towards a more efficient and better accepted enforcement of speed limits?", vol. 5ETS Speed Fact Sheet, Etterbeek, Belgium, 2009.

[5] M. H. Cameron, "Development of strategies for best practice in speed enforcement in western Australia," Supplementary Report, Monash University Accident Research Centre, Melbourne, Australia, 2008.

[6] K. Charlesworth, "The effect of average speed enforcement on driver behaviour," in Proceedings of the Road Transport Information and Control-RTIC 2008 and ITS United Kingdom Members’ Conference, IET, Manchester, UK, May 2008.

[7] C. Stefan and M. Winkelbauer, Section Control–Automatic Speed Enforcement in the Kaisermühlner Tunnel (Vienna, A22 Motorway), Kuratorium für Verkehrssicherheit, Vienna, Austria, 2006.

[8] H. Stoehlhorst, "Reduced speed limits for local air quality and traffic efficiency," in Proceedings of the European Congress and Exhibition on Intelligent Transport Systems and Services, Geneva, Switzerland, June 2008.

[9] V. Punzo and E. Cascetta, "Impact on vehicle speeds and pollutant emissions of the fully automated section speed control scheme safety tutor on the naples urban motorway," in Proceedings of the Paper Presented at the SIDT - Scientific Seminar - External Costs of Transport Systems: Theory and Applications, Rome, Italy, 2010.

[10] E. Cascetta and V. Punzo, "Impact on vehicle speeds and pollutant emissions of an automated section speed enforcement system on the Naples urban motorway," in Proceedings of the Transportation Research Board 2011 Annual Meeting, vol. 17, Washington, DC, USA, January 2011.

[11] A. Montella, L. L. Imbriani, V. Marzano, and F. Mauriello, "Effects on speed and safety of point-to-point speed enforcement systems: evaluation on the urban motorway A56 Tangenziale di Napoli," Accident Analysis & Prevention, vol. 75, pp. 164–178, 2015.

[12] A. Montella, V. Punzo, S. Chiaradonna, F. Mauriello, and M. Montanino, "Point-to-point speed enforcement systems: speed limits design criteria and analysis of drivers’ compliance," Transportation Research Part C: Emerging Technologies, vol. 53, pp. 1–18, 2015.

[13] H. Lahrmann, B. Brassae, J. W. Johansen, and J. C. O. Madsen, "Safety impact of average speed control in the UK," Journal of Transportation Technologies, vol. 6, no. 5, pp. 312–326, 2016.

[14] M. Borsati, M. Cascarano, and F. Bazzana, "On the impact of average speed enforcement systems in reducing highway accidents: evidence from the Italian Safety Tutor," Economics of Transportation, vol. 20, p. 100123, 2019.

[15] D. Y. Kim, H. W. Lee, and K. S. Hong, "A study on effectiveness analysis and development of an accident prediction model of point-to-point speed enforcement system," Journal of the Korean Society of Safety, vol. 34, no. 5, pp. 144–152, 2019.

[16] D. W. Soole, B. C. Watson, and J. J. Watson, "Effects of average speed enforcement on speed compliance and crashes: a review of the literature," Accident Analysis & Prevention, vol. 54, pp. 46–56, 2013.

[17] A. Montella, B. Perpold, M. D’Apuzzo, and L. L. Imbriani, "Safety evaluation of automated section speed enforcement system," Transportation Research Record: Journal of the Transportation Research Board, vol. 2281, no. 1, pp. 16–25, 2012.

[18] A. Høye, "Safety effects of section control—an empirical Bayes evaluation," Accident Analysis and Prevention, vol. 74, pp. 169–178, 2015.

[19] E. Hauer, "Observational before/after studies in road safety," Estimating the Effect of Highway and Traffic Engineering Measures on Road Safety, Elsevier Science Ltd., Oxford, UK, 1997.

[20] J. Shim, K. Jang, S. H. Park, H.-S. Lee, H. Yeo, and O. H. Kwon, "Evaluating safety performance of climbing lane configurations on South Korean expressways," Transportation Research Record, vol. 2583, 2016.

[21] R. Elvik, "The predictive validity of empirical Bayes estimates of road safety," Accident Analysis & Prevention, vol. 40, no. 6, pp. 1964–1969, 2008.

[22] O. H. Kwon, Y. Yoon, and K. Jang, "Evaluating the effectiveness of the law banning handheld cellphone use while driving," Safety Science, vol. 70, pp. 50–57, 2014.

[23] U. Brüde and R. Elvik, "The turning point in the number of traffic fatalities: two hypotheses about changes in underlying trends," Accident Analysis & Prevention, vol. 74, pp. 60–68, 2015.

[24] C. Chen, Freeway Performance Measurement System (PeMS). Research Reports, California Partners for Advanced Transit and Highways (PATH), Institute of Transportation Studies (UCB), Berkeley, CA, USA, 2003.

[25] C. F. Daganzo, Fundamentals of Transportation and Traffic Operations, Elsevier Science Inc., New York, NY, USA, 1997.

[26] J. L. Fleiss, B. Levin, and M. C. Paik, "The analysis of data from matched samples," Statistical Methods for Rates and Proportions, pp. 373–406, John Wiley & Sons, Inc., Hoboken, NJ, USA, 3rd edition, 1981.

[27] H. Yeo, K. Jang, A. Skabardonis, and S. Kang, "Impact of traffic states on freeway crash involvement rates," Accident Analysis & Prevention, vol. 50, pp. 713–723, 2013.

[28] C. Oh, S. Park, and S. G. Ritchie, "A method for identifying rear-end collision risks using inductive loop detectors," Accident Analysis & Prevention, vol. 38, no. 2, pp. 295–301, 2006.

[29] K. Chung, K. Jang, S. Oum, Y. Kim, and K. Song, "Investigation of attributes of kinematic waves preceding traffic collisions," in Proceedings of the 17th ITS World Congress, Busan, South Korea, October 2010.

[30] M. Abdel-Aty, J. Dilmore, and L. Hsia, "Applying variable speed limits and the potential for crash migration," Transportation Research Record: Journal of the Transportation Research Board, vol. 1953, no. 1, pp. 21–30, 2006.

[31] T. F. Golob, W. W. Recker, and V. M. Alvarez, "Freeway safety as a function of traffic flow," Accident Analysis & Prevention, vol. 36, no. 6, pp. 933–946, 2004.

[32] G. X. Liu and A. Popoff, "Provincial-wide travel speed and traffic safety study in saskatchewan," Transportation Research Record: Journal of the Transportation Research Board, vol. 1595, no. 1, pp. 8–13, 1997.

[33] S. Park, K. Jang, S. H. Park, D.-K. Kim, and K. S. Chon, "Analysis of injury severity in traffic crashes: a case study of Korean expressways," KSCE Journal of Civil Engineering, vol. 16, no. 7, pp. 1280–1288, 2012.