Investigating Regression-to-the-Mean in Before-and-After Speed Data Analysis

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Abstract

Regression-to-the-Mean (RTM) in before-and-after speed data is a purely statistical phenomenon that makes random variation in repeated speed measurements from multiple time points before and after the introduction of an engineering treatment look like a genuine speed change brought about by the engineering treatment. This study shows that an observational before-and-after speed data analysis cannot collect speed measurements without measurement error and cannot be free from RTM bias. If we are to obtain accurate estimates of the magnitude of the mean speed change brought about by an engineering treatment, we need to reduce RTM bias. This study first uses a graphical method to illustrate the RTM phenomenon, and then uses numerical examples (with aggregated speed data) to show how to reduce RTM bias in before-and-after speed data analysis. The numerical examples show that the estimated magnitude of the mean speed change due to the introduction of an engineering treatment and/or the amount of uncertainty (measured by the estimated standard error and confidence interval) associated with the mean speed change can be misleading if we fail to take RTM properly into account. The paper concludes with suggestions for more rigorous statistical methods, preferably suited for use with disaggregate speed data, that may help to reduce RTM bias in future speed data analysis.
INTRODUCTION

After Galton’s (1) groundbreaking discovery of the Regression-to-the-Mean (RTM) phenomenon more than a century ago, numerous researchers in various disciplines have investigated this purely mathematical phenomenon and have analyzed its impact on the estimation of treatments effect (2-4). Galton originally reported that two tall plants would produce offspring plants which were, on average, shorter than either parent plant. He also noticed the same phenomenon in humans (4-5). A naïve or informal explanation of the RTM phenomenon can be generated from Galton’s findings by stating that if the first observation in a series of data selection is either higher or lower than the long term mean (or population mean) value of an entity (or entities), the expected value of the second observation is closer to the long term mean (or population mean) value of the entity (or entities) than the first observed value in the data selection process.

The RTM phenomenon has also been well recognized by transportation safety researchers and practitioners, and discussed in many publications (6-10). As a result of the extensive discussion, RTM is now an established concept among traffic safety researchers. We recognize that if we estimate treatment effects using a simple before-and-after comparison of accident frequencies without properly taking the RTM phenomenon into account, we are likely to obtain an inflated (or deflated) estimate of the target treatments effect.

Transportation engineers do not rely only on accident frequency. We also rely heavily on the mean speed and/or a certain percentile speed (e.g. 85th percentile speed) as a measure to estimate the operational and/or safety performance of target treatments for various purposes. For example, transportation engineers commonly use a diverse range of speed measures to estimate the amount of reduced delay time and/or potential decrease in vehicles’ operational speeds brought about by the introduction of Intelligent Transportation System (ITS) technologies. We typically compare the observed and/or estimated speed measures before and after the introduction of a certain ITS technology at target locations. Examples include the evaluation of: dynamic curve warning systems (11), adverse visibility information systems (12), automated speed enforcement cameras (13), and variable speed limit signs (14). Speed measures have also been used to evaluate conventional non-ITS related treatments such as the posted speed limit (15) and centerline rumble strips (16).

In particular, one of the reasons for the popularity of speed as a safety performance measure may be the lack of accumulated accident history available from the short period after the implementation of engineering treatments at target roadway sections or locations. Whereas accident frequency, often requires waiting for several years before accumulating the necessary amount of accident data for evaluating treatments, transportation engineers can collect a relatively large amount of speed data using various speed data collection tools (e.g. radar guns, loop detectors) within a very short time period after the introduction of engineering treatments (e.g. in a few days or a week). Engineers then compare the chosen speed measures (e.g. mean speed, speed variance) before and after the implementation of engineering treatments, and estimate the magnitude of speed change using various statistical methods, such as the student t-test, Wilcoxon signed-rank test, and linear regression analysis.

As we will discuss in detail in a later section of this paper, RTM, which usually also includes the phenomenon of Regression Against the Mean (RAM; the opposite phenomenon of RTM), is a ubiquitous phenomenon that occurs whenever individual entities or groups of entities are measured at different time points in time unless the successive measurements at the different
time points show a perfect correlation with each other. In other words, the RTM is caused by the
imperfect (temporal) correlation between the same observation measured at different points in
time; the smaller the correlation (below 1), greater is the RTM (4). It should be pointed out that a
perfect correlation is a practically unachievable statistical property in observational studies (17).
Thus, it is anticipated that RTM will always exist when repeated measurements are used as part
of the analysis protocol and, in the end, what will change is the magnitude of the RTM.
Furthermore, the RTM should not be confused with the selection effects or bias, as discussed by
Cook and Wei (18) (this issue is discussed further below).

Unfortunately, however, no transportation engineering studies that focused on a before-
and-after speed comparison analysis have attempted even to consider the potential RTM bias in
the estimation of the magnitude of speed change. (It is also possible that some transportation
engineers do not know what questions to ask as they may not fully acknowledge the possibility
of RTM bias in a before-and-after speed data analysis.)

This study has the following two specific objectives:

1) Describe RTM using a graphical method, and introduce a more rigorous definition of
RTM in an observational before-and-after analysis that focuses on speed data analysis.

2) Demonstrate an approximation method that can a) take RTM into account in
aggregate speed data analysis, and b) show how to reduce the amount of potential
RTM bias in the estimation of magnitude of mean speed change.

To accomplish the objectives of this study, we first apply a graphical examination used
by Campbell and Kenny (17) and Finney (19) to clarify what RTM represents, and to introduce a
more rigorous definition of RTM. We then apply Chuang-Stein’s method (20), and show how to
estimate magnitude of speed change after taking the RTM into account. The end goal of this
study is to alert transportation engineers to the problem of RTM bias in speed data analysis, and
to provide clear motivation for developing more genuine speed comparison methods that can be
widely applied in future transportation engineering practice.

REGRESSION TO THE MEAN

Figure 1 shows hypothetical speed measurements collected from 22 different sites in two time
periods. The two time periods refer to before and after the introduction of an engineering
treatment, and are denoted as Yb and Ya, respectively. We assume that the speed measurements
from the two different time periods follow a bivariate normal distribution with mean values μb
and μa and standard deviations σb and σa, respectively, with correlation coefficient ρ. If we
further assume an additive treatment effect based on the mean speed change from the “before” to
the “after” time period, the treatment effect (i.e. the magnitude of mean speed change in our
case) can be represented as “τ = μa - μb”. In this case, the expected value of Ya given Yb can be
expressed as (21):

$$\hat{Y}_a = E[Y_a | Y_b] = \mu_b + \tau + \rho \frac{\sigma_a}{\sigma_b} (Y_b - \mu_b)$$ (1)

Theoretically, if there is absolutely no treatment effect (i.e. the magnitude of the mean
speed change = 0) before and after the introduction of an engineering treatment, and if the speed
measurements in the before-treatment time period can be perfectly re-measured in the after-
treatment time period with no measurement error, then $\mu_b = \mu_a = \mu$ and $\sigma_b = \sigma_a = \sigma$. More importantly, in this circumstance, the correlation ($\rho$) between the two speed measurements from the two time periods will be exactly equal to 1 (hence, no RTM). Recall that the correlation can be calculated using equation (2):

$$\rho_{Y_a,Y_b} = \frac{COV(Y_a,Y_b)}{\sigma_{Y_a} \sigma_{Y_b}}$$

The 11 black circles in Figure 1 represent the speed measurements that are assumed to be measured in this hypothetical circumstance. The speed measurements lie on a solid diagonal line, representing the perfect-correlation line. In this case, the predicted speed values ($\hat{Y}_a$) and the observed speed values ($Y_a$) in the after-treatment time period are equal to the observed speed values in the before-treatment time period ($Y_b$). Since the expected speed values are perfectly equal to the observed speed values in the after-treatment time period, we would not expect any RTM bias in this hypothetical circumstance. In other words, RTM does not exist if, and only if, the magnitude of correlation ($\rho$) based on repeated (speed) measurements before and after treatment implementation is equal to 1 (17).

Now, consider more realistic circumstances in which the speed measurements from before and after the treatment do not lie exactly on the perfect correlation line. In fact, the speed measurements cannot be perfectly reproduced in the two different time periods perhaps because of the different demography of the study population (e.g. different drivers, vehicles, and trip purposes), temporal changes, and the inevitable measurement errors. The 11 gray diamonds in Figure 1 represent this second set of more realistic hypothetical speed measurements. We continue to assume no treatment effect (i.e. $\mu_b = \mu_a$) and a common standard deviation (i.e. $\sigma_b = \sigma_a = \sigma$) for illustration purpose. (We relax these assumptions in a later section when we discuss numerical examples.) However, the correlation ($\rho$) between the speed measurements from the two time periods in Figure 1 can be less than 1, but greater than 0. The dashed line in Figure 1 can be regarded as a usual form of a linear regression model that can predict $Y_a$, given $Y_b$ (i.e. $\hat{Y}_a = \beta_0 + \beta_1 \cdot Y_b$). The dashed line represents the predicted values in the after-treatment period when RTM is taken into account.

In this second hypothetical situation, an observed speed of, for example, 65 mph in the before-treatment time period would result in a predicted value of less than 65 mph in the after-treatment time period (i.e. the predicted value would be regressed towards the mean). On the other hand, the predicted speed conditional on the observed speed 55 mph is moved upwards, and is estimated as more than 55 mph (i.e. the predicted value would again be regressed towards the mean). As explained in Campbell and Kenny (17), the RTM effect can be defined as the vertical distance between the perfect-correlation line (the solid line in Figure 1) and the regression line (the dashed line in Figure 1), and we readily notice that the higher (or lower) the observed speeds, the greater the RTM effect. Furthermore, since we still assume a common standard deviation (i.e. $\sigma_b = \sigma_a = \sigma$) for the speed measurements from the two different time periods, the slope of the linear regression model [i.e. $\beta_1 = \rho (\sigma_a / \sigma_b)$] simply becomes the correlation coefficient ($\rho$). We conclude that a) the lower the magnitude of correlation ($\rho$) between the two measurements (in our case, speed measurements) in the before and after treatment periods, the greater the RTM, and b) anything else (e.g. measurement error) that makes
the magnitude of correlation less than 1 will contribute to the generation of a certain degree of RTM.

Campbell and Kenny (17) also described RTM as simply “a tautological restatement of imperfect correlation” between repeated measurements over time. Thus, asking whether RTM occurs in a before-and-after speed comparison analysis is equivalent to asking whether the correlation between speed measurements from two time periods is equal to 1. Similarly, asking the magnitude of RTM is the same as asking the magnitude of the correlation between the two speed measurements over the two time periods.

**NUMERICAL EXAMPLES**

**Example Based on Muchuruza and Mussa’s 2004 Study**

Imagine a jurisdiction decides to increase the posted speed limit from 65 mph to 70 mph on selected sections of rural highways, and expects that the increased posted speed limit of 5 mph will likely increase vehicles’ travel speed by 5 mph (or more) on average for the targeted sections. The increase in posted speed limits is expected to reduce travel time although some studies have shown this could negatively affect safety (22). Further imagine that the jurisdiction collects speed data from each section of highway before and after increasing the speed limit by 5 mph. Later, the jurisdiction uses the “student t-test” to confirm that the 5 mph mean speed increase is statistically significant. This approach might be marginally acceptable if, and only if, our aim is to estimate the magnitude of the mean speed increase. If we use this approach, we would be assuming that the speed measurements from the two different time periods are collected randomly and independently from normally distributed populations. These assumptions are very commonly made by transportation researchers who regularly conduct a before-and-after speed data analysis, but as we have already discussed in this paper, the following issues remain unrealistic. Firstly, RTM is inevitable when collecting speed measurements from different time periods as a perfect correlation between the measurements is unachievable. Secondly, the degree of RTM will vary with the magnitude of the correlation, and will therefore be different from one dataset to another dataset collected from different sites.

As a first numerical example, we use before-and-after speed data reported in Muchuruza and Mussa’s study (23) to illustrate possible RTM bias in the estimated mean speed change and/or the standard errors of the estimated mean speed change. Before discussing Muchuruza and Mussa’s data, we clearly note that the main purpose of their study was not to examine the amount of mean speed change. Their study focused on investigating the amount of speed variation caused by increasing posted speed limit from 65 mph to 70 mph. Their study’s approach and findings remain legitimate for their study purposes, and the discussion here is not intended to question their findings.

Muchuruza and Mussa’s study (23) collected mean speed data on various sections of major interstate highways (4 and 6 lanes) in Florida in 1996 when the posted speed limit was 65 mph. They selected sites that show the highest free-flow speed possible (i.e. non-random site selection). The study collected mean speed data again after the posted speed limit was increased to 70 mph in 2002. The reported mean speed from 8 different sections of 6-lane interstate highways in Florida is shown in the second and the third column in Table 1. The fourth column in Table 1 and the black triangles in Figure 2 represent the difference in the observed mean speed between the two measurement time periods (i.e. $\delta = Y_a - Y_b$).
We observe the following:

1. All 8 individual sections of highways show an increase in the observed mean speed. The increase ranges from 3 to 9 mph with an average speed increase of 5.88 mph.

2. The estimated standard error of the observed mean speed increase is estimated as 0.85 (= 2.42 / √8), resulting in a 95% confidence interval of 4.17 – 7.58 mph. (We note that the estimated standard error is calculated as “s/√n”, where s = standard deviation of point estimates reported in Table 1, and n = number of observations.)

3. The magnitude of the speed increase seems greater for the highway sections with lower initial mean speeds, and vice versa. In other words, the magnitude of speed change seems to be greater for the highways sections with the lower observed mean speeds in the before-treatment time period, and vice versa. For instance, the 9 mph increase is on Section No. 6 where the initial mean speed was 63 mph (the lowest observed mean speed of the 8 highway sections) whereas the 3 mph increases are on Sections No. 3 and 7 where the initial mean speeds were 68 mph and 69 mph respectively (the two highest observed mean speeds).

The most subtle issue is the third one. Intuitively, it does make sense to expect that the highway sections with the lowest initial mean speed before increasing the speed limit would experience the highest speed increases. This would imply that highway sections where the mean speed is already very close to the new speed limit (70 mph) would not experience the same (or greater) amount of speed increase as highway sections that had a lower initial mean speed. The few researchers (24, 25) who have noted this varying treatment effect have called it the differential effect. Many researchers, however, have not clearly distinguished the differential effect from the RTM effect, and have simply represented the mixed effect of the two effects as the RTM effect. If we describe the differential effect in our first numerical example, we can say that the magnitude of the speed change that is different from one highway section to another highway section arises because of the magnitude of the initial speed of each highway section and because of the unequal variance in speed measurements in the before-and-after time periods.

Recall the one of the most popular descriptions of RTM by Campbell and Kenny (17) in an earlier section of this paper. They point out that the degree of RTM is related to the magnitude of correlation (ρ) between speed measurements over time with the assumption of equal variance in multiple measurements over time (i.e. σ_a/σ_b = 1).

Nonetheless, the real issue here is that the differential effect that is due, for example, to the unequal variance often exacerbate the RTM bias. As a result, researchers may conclude that the magnitude of mean speed change for the highway sections investigated is much greater than is really the case: the greater magnitude in the estimated speed change could simply be a reflection of the mixed effects of the differential and the RTM effect.

Once again, we use the speed measurements from the before (Y_b) and after (Y_a) treatment periods (i.e. treatment = posted speed limit in this example). These speed measurements are assumed to follow a bivariate normal distribution with mean speeds μ_b and μ_a, and standard deviations σ_b and σ_a respectively, and correlation (ρ). We also present the observed speed change from the before period to the after period as δ = Y_a - Y_b.
According to Bonate (26), Chuang-Stein (20) established the following post-hoc procedure that can approximate the magnitude of the mean speed change after the adjustment for the RTM effect. The procedure starts with the estimation of the speeds in the after-treatment time period after adjusting for the RTM effect ($\hat{Y}_a^*$). For example:

$$\hat{Y}_a^* = Y_a - \theta(\rho - 1)(Y_b - \mu_b)$$  \hspace{1cm} (3)

where, $\theta = \sigma_a / \sigma_b$

The expected mean speed change after adjusting for the RTM effect ($\hat{\delta}^*$) is then expressed as:

$$\hat{\delta}^* = \hat{Y}_a^* - Y_b$$  \hspace{1cm} (4)

In equation (3), the magnitude of $\rho$ is related to the degree of the RTM effect, and the magnitude of $\theta$ is related to the degree of the differential effect. If $\sigma_b = \sigma_a$ in equation (3), then the differential effect will not be an issue, and we can shorten equation (3) by deleting “$\theta$” in the expression. Since, however, there is no guarantee that the speed variance will not be changed by the introduction of an engineering treatment to a site, we need to test whether or not we can safely ignore $\theta$ in equation (3).

Berry et al. (24) introduced Pitman’s (27) equal variance test for two measurements from different time periods to test for a differential effect, and to help to isolate the effect of RTM. The differential effect can be tested by the following test statistics with the null hypothesis $H_0$: $\sigma_b = \sigma_a$ against its alternative $H_1$: $\sigma_b \neq \sigma_a$.

$$T_p = \frac{\sqrt{n - 2\left[(s_b / s_a) - (s_a / s_b)\right]}}{2\sqrt{1 - \gamma^2}}$$  \hspace{1cm} (5)

This test statistics follows a student’s t-distribution with “n-2” degrees of freedom, where $n = $ the sample size, and where $\gamma$, $s_b$, and $s_a$ are the common unrestricted maximum likelihood estimates of $\rho$, $\sigma_b$, and $\sigma_a$, respectively.

The analysis of Muchuruza and Mussa’s (23) data in Table 1 provides marginal evidence for a differential effect ($T_p = 1.891$, d.f. = 6, $P = 0.054$) at the 95% confidence level. Thus, we are unable to ignore the effect of “$\theta$” in our example case. We also estimated the mean speed change after the adjustment for RTM using equations (3) and (4). The result is presented in the last column in Table 1, and as white circles in Figure 2. The dashed line in Figure 2 represents the predicted mean speed change after the RTM adjustment. The line shows that the degree of statistical association between the initial mean speeds and the predicted mean speed change has been greatly reduced after the adjustment for RTM bias in the speed data. The estimated magnitude of the mean speed change is 5.88 mph, and this value is statistically significant using a two-sample t-test with unequal variances (i.e. the Smith-Satterthwaite t-test) at the 95% confidence level before and after the adjustment for RTM bias. The estimated standard error relating to the mean speed change has, however, been reduced considerably (S.E. = 0.42 mph) after adjusting for RTM bias, resulting in a 95% confidence interval of 5.04 - 6.71 mph. This means that, compared to the mean values obtained before adjusting for RTM bias an extreme initial mean speed (whether very low or very high) does not produce an inflated magnitude of speed change after adjusting for RTM.
Example Based on Monsere et al.’s 2005 Study

The second numerical example uses the observed mean speed change data before and after the introduction of a Dynamic Curve Warning System (DCWS) on an interstate highway in Oregon State. We use selected speed data originally presented by Monsere et al. (11) only to show that RTM could affect the estimated magnitude of the mean speed change after the introduction of an engineering treatment. Once again, we clearly note that the main purpose of the Monsere et al.’s study was not to examine the magnitude of speed change using an aggregate speed data analysis. Monsere et al. investigated the magnitude of speed change for individual sites separately (i.e. they used disaggregate speed data analysis). We do not question their study approaches and/or their findings.

In this study, we use selected speed data from Table 3 of Monsere et al.’s study. Originally, Monsere et al. collected speed data from selected sites that show higher than average accident rate in the Oregon State (i.e. non-random site selection). We use 8 out of the 10 examples of speed data for “Northbound Commercial Vehicles.” The results of our analysis are presented in Table 2 and Figure 3. As in our analysis of the Muchuruza and Mussa (23) data, we conducted Smith-Satterthwaite’s two-sample t-test with unequal variances. Strictly speaking, the result shows that the mean speed change after taking into account RTM ($\hat{\delta} = -1.83$ mph) is not statistically significant at the 95% confidence level ($T = -1.762$, d.f. = 12, $P = 0.052$), but the $P$ value is very close to its marginal acceptance level of 0.05. The mean speed change value was statistically significant in its original magnitude of speed change ($\delta^*$) ($T = -1.815$, d.f. = 11, $P = 0.048$) at the 95% confidence level. As a result, strictly speaking, there is no evidence to expect that a 1.83 mph speed reduction will occur for the commercial vehicles in the target section of interstate highway after the introduction of DCWS. A certain degree of the mean speed change is affected by the RTM.

The magnitude of the estimated standard errors of the mean speed change (0.43) is also slightly reduced after consideration of RTM compared to the magnitude of the estimated standard errors of the observed mean speed (0.49). This results in a reduced range for the confidence interval of the mean speed change (-2.69 ~ -0.96 mph) compared to the range for the confidence interval of the original mean speed change (-2.80 ~ -0.85 mph).

DISCUSSION

RTM has a long history of discussion in various disciplines, but recognition of the RTM phenomenon and its potentially negative impact on the validity of traffic data analysis in the transportation engineering field (e.g. speed data analysis and accident data analysis) is sometimes too vague and informal to qualify as a full description or generalization of the RTM phenomenon. As the site selection bias is outside of the scope of this paper, this study intentionally avoided discussing site selection effects and its implications for RTM bias, but transportation engineers often refer to “non-random site selection” when acknowledging the RTM issue; as discussed above, the sites were not randomly selected. It should be pointed out that even when the RTM is minimized or corrected, site selection could be still influence the effects of a treatment (18). This tendency could give the false impression that the random selection of study sites may resolve all the issues relating to RTM bias. In reality, we should recognize that a certain amount of Regression-to-the-Mean (or Regression-against-the-Mean) is almost inevitable in a longitudinal data analysis as this type of analysis requires multiple data points during the study time period(s).
No transportation engineering studies, including the recent operational and safety evaluation studies of ITS technologies, have fully considered the potential impact of RTM in before-and-after speed data analysis. This study is intended to stimulate discussion about RTM among transportation engineers, and to bring the attention of transportation engineers to the following points:

1. In general, we agree with the view that observations measured at different points in time, such as those done in before-after studies, will be influenced by the RTM bias. In fact, RTM is an omnipresent and inevitable phenomenon whenever we use measurements (e.g. mean speed, accident frequency) from multiple time periods to evaluate an engineering treatment. The problem of RTM bias arises because of the imperfect correlation between the repeated measurements from different time periods. We can always expect that there will be a certain amount of measurement error inherent in speed data collection methods/tools, and we can also always expect that there will be a certain level of difference in the roadway and traffic environment over the two measurement times (e.g. differences in vehicles, drivers, trip purposes). All these factors will contribute to a less-than-perfect correlation between measurements from different times.

2. We introduced an approximation method that can test and estimate the magnitude of mean speed change that remains after reducing RTM bias. The method was originally suggested by Chuang-Stein (20) and assumes normality in (speed) measurements over time. Park et al. (28), however, noted that such an assumption may not be valid in every circumstance. As a result, the magnitude of the mean speed change after the adjustment of RTM presented in this paper may not reflect the true value of the mean speed change. We need to acknowledge that RTM will appear regardless of the distributional form of the speed measurements unless the speed measurements for the two time periods show perfect correlation with each other.

3. In our numerical examples, RTM commonly amplified the estimated standard errors of the mean speed change, and therefore increased the confidence interval for the estimated magnitude of the mean speed change.

4. In order to check whether the estimated mean differences before-and-after RTM adjustment (i.e. $\delta$ and $\hat{\delta}^*$) are statistically significant values or not, we applied the Smith-Satterthwaite t-test. The Smith-Satterthwaite t-test not only uses the mean value of the speed difference as an input value but also uses the variance (standard deviation) of the speed difference as an input value. The second numerical example in this paper (i.e. Monsere et al.’s study) failed to pass the test if we use the RTM adjusted speed difference ($\hat{\delta}^*$); this means that the estimated mean speed difference ($\hat{\delta}^*$) after the adjustment of RTM is not statistically significant. Therefore, we can speculate that RTM may contribute to the inflation of the estimated magnitude of mean speed change associated with an engineering treatment in certain circumstances. We note that the method originally proposed by Chuang-Stein (20) does not automatically show us the unbiased mean value by removing the inherent RTM bias in the mean value. The Chuang-Stein method shows us whether the estimated mean value is statistically significant or not.
5. We note that this paper’s approximation method for adjusting RTM bias in speed data is not the best method available in engineering practices for reducing RTM bias. We used this method mainly because we were unable to obtain a previous study with a dataset that contains disaggregated speed measurements (e.g. speed data for each individual vehicle for each study site over the study period). Because of this restriction, we made the strong assumption of a common mean speed value ($\mu_b$) to represent the mean speed of various sites in the two numerical examples in the previous section. In reality, however, there could be a systematic difference in mean speed values from a study site to another study site. For instance, the systematic difference in speeds could be attributed to confounding factors inherent in speed data (e.g. behavioral adaptation of the speed limit, enforcement, changes in the travel patterns). Unfortunately, given the data we used, we are not in a position to estimate all these effects.

Despite the limitations that we acknowledge, we believe that the contribution made by this paper can be regarded as the first attempt to ring a warning bell to transportation engineers about the potential for RTM bias in estimates of the magnitude of the (mean) speed change before and after the introduction of an engineering treatment.

Future work should continue to investigate and develop a method that can accurately quantify the magnitude of the (mean) speed change brought about by an engineering treatment. The method developed should not be limited to the aggregated speed data (mean speed) used in this study, but should be suitable for direct use with disaggregate speed data obtained from the speed of individual vehicles at various study sites. Candidate methods include, but are not limited to, the Analysis of Covariance (ANCOVA) (5, 29) and multilevel analysis (a.k.a. hierarchical data analysis) (30). Finally, the proposed method should also incorporate the bias introduced by the selection effects. The procedure proposed by Cook and Wei (18) could be useful in this regards.

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All units in this table are mph.
TABLE 2 Before-and-after mean speed data from Monsere et al. (2005)

<table>
<thead>
<tr>
<th>Highway Section No.</th>
<th>( Y_b )</th>
<th>( Y_a )</th>
<th>( \delta = Y_a - Y_b )</th>
<th>( \delta^* = \hat{Y}_a^* - Y_b )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>54.00</td>
<td>49.30</td>
<td>-4.70</td>
<td>-4.48</td>
</tr>
<tr>
<td>2</td>
<td>53.40</td>
<td>50.90</td>
<td>-2.50</td>
<td>-2.32</td>
</tr>
<tr>
<td>3</td>
<td>53.20</td>
<td>50.80</td>
<td>-2.40</td>
<td>-2.24</td>
</tr>
<tr>
<td>4</td>
<td>52.30</td>
<td>50.70</td>
<td>-1.60</td>
<td>-1.50</td>
</tr>
<tr>
<td>5</td>
<td>48.70</td>
<td>47.90</td>
<td>-0.80</td>
<td>-0.97</td>
</tr>
<tr>
<td>6</td>
<td>48.20</td>
<td>47.90</td>
<td>-0.30</td>
<td>-0.51</td>
</tr>
<tr>
<td>7</td>
<td>48.90</td>
<td>47.70</td>
<td>-1.20</td>
<td>-1.36</td>
</tr>
<tr>
<td>8</td>
<td>49.20</td>
<td>48.10</td>
<td>-1.10</td>
<td>-1.23</td>
</tr>
</tbody>
</table>

Average 50.99 49.16 -1.83 -1.83  
Standard Deviation 2.45 1.44 1.38 1.23

All units in this table are mph.
FIGURE 1 Predicted speed lines from perfectly and imperfectly correlated before-and-after speed measurements
FIGURE 2 Magnitude of speed change based on Muchuruza and Mussa’s (2004) study
FIGURE 3 Magnitude of speed change based on Monsere et al’s (2007) study