Speed and Safety

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The speed at which people elect to travel is affected by vehicle and road design; by limits to speed and enforcement of those limits; by traffic control, signs, and markings; and so forth. The speed at which people travel, in turn, affects road safety. In this context two questions arise: (a) How is the evolution of speed over time and space affected by what drivers do? (b) How does speed affect safety? This paper reviews what is known, notes the gaps in knowledge, and describes where opinions differ and why. Unfortunately, despite decades of speed measurement and monitoring, the evolution of speed over time is poorly documented, and the understanding of what drives the evolution is largely missing. It is known that speeds evolve over time, but not why; it is known that there is some spillover of the change from one road to another, but its size or extent cannot be predicted. This is a neglected field of inquiry. More is known in answer to Question b. There can be no reasonable doubt that if speed increases while other conditions (vehicles, roads, medical services) remain unchanged, the accidents that occur will tend to be more severe. However, the prevalent and strongly held belief that the greater the speed, the higher is the probability that accidents will occur is, at present, not well supported by research. Even so, given a change in mean speed, one can predict the consequences in injuries and fatalities and this paper discusses how to do so.

The relationship between speed and safety is subject to much debate. Opinions are strongly held and much heat is generated around the dinner table, in the media, on the pages of professional and scientific publications, and, of course, in politics. The essence of the situation is a two-link causal chain in which the arrow represents the word “affects”:

Some of what people do (by vehicle design and advertising, by road design, by setting speed limits and enforcing them, etc.) → speed choice → road safety.

These two causal links raise two questions:

Question 1. How does what we do shape the evolution of speeds on roads?
Question 2. How does speed affect safety?

These are the main questions discussed in this paper. The purpose is to review what can be regarded as “known,” to note where the gaps in knowledge are, and to state where opinions differ and why.

EVOLUTION OF SPEED

Figure 1 shows the time evolution of speed on the rural interstates in Montana. The horizontal axis is in quarterly units, except for the years 1982 to 1986 and for the “gap” years (1986 to 1995) where no speed data were collected, and the increments are annual. The solid line is for the 85th percentile and the dashed line for the median speed. Between 1979 and April 1987, the speed limit was 55 mph. From there until December 1995, the speed limit was raised to 65 mph. Whether there was a jump in April to May 1987 cannot be said because data collection stopped until 1995. A backward extrapolation of the later trend indicates that a jump in speed likely occurred. In December 1995 Montana adopted the “Basic Rule,” which prevailed until the end of May 1999. According to the Basic Rule, daytime speeds should not exceed what is “reasonable and prudent” in a police officer’s judgment, while the nighttime speed limit remained at 65 mph. On May 28, 1999, Montana abandoned the Basic Rule and raised the speed limit to 70 mph.

Figure 1 represents a phenomenon that is evolving over time. The left half of the figure, in particular the period 1981 to 1999, shows a steady upward creep in speed that, over the nearly two decades, amounted to 10 to 15 mph. What was the cause of this creep which continued even during times when the speed law and the road remained the same? There must have been influences other than a change in speed limit. Then, sometimes in 1998, even before the Basic Rule gave way to the 70 mph speed limit, the upward creep seems to have slowed down and stopped. What has changed? Is this kind of speed evolution typical in other states or countries? Is it characteristic of all road types or confined to rural access-controlled roads? What drives the upward creep and what stops it? These are weighty questions that do not seem to have received much attention. One can easily imagine various mechanisms that might contribute to the apparent upward drift in speeds.

One such mechanism could be the practice of setting the speed limit by the 85th percentile of the speed distribution. For example, assume that collectively drivers elect speeds such that about half of them drive faster than the speed limit. This behavior, if coupled with a periodical application of the 85th percentile rule, would cause an upward drift in speeds as illustrated in Figure 2.

The dashed curve depicts the speed distribution with the prevailing speed limit of 70 km/h. When the speed limit is raised to 90 km/h to be in line with the 85th percentile rationale, then, by the assumed behavior, the solid curve will gradually form. This, in turn, will justify the next round of speed limit adjustments, and so on.

Another behavioral mechanism affecting speed choice could be rooted in the self-image of drivers. Research shows that the majority of drivers believe that they are better than average drivers. One way to confirm this self-image is by driving faster than the average speed. If the majority of drivers try to be faster than the average, speeds must continuously increase.

A third possible mechanism might be the building of wider roads. As lanes become wider, travel becomes faster, as was shown.
by Fitzpatrick et al. (1). Therefore, as wider lanes become more prevalent, the average speed increases.

The time profile in Figure 1 is but one anecdote and the speculation it may engender has no natural end. To be on solid ground, the evolution of speed by road type, environment, and jurisdiction must first be documented and then explained by systematic inquiry.

In addition to questions about how speed evolves over time, there are questions about how speed evolves over space. Is it true that if the speed changes on one kind of road, some of the change will spill to other roads too? Is the spillover limited to nearby roads or does it change norms of behavior more generally? These questions were investigated by Casey and Lund (2, 3). The authors found that “allowing higher speeds on some highways...causes higher speeds on local, connecting roads through speed adaptation.” They also claim that allowing higher speed on some highways “may cause higher speeds on other, unconnected and distant roads through some indirect process of speed generalization.” This latter conclusion is somewhat tenuous because the general increase in speed over time may have been caused by many factors, not only the increase in speed limits. At present not enough is known about the spillover and adaptation phenomena to allow one to predict the size and extent of the effect.

As will be argued later, one cannot reasonably believe that the pre-crash speed has no effect on the severity of crashes. If precrash speed matters to safety, then one ought to understand how what profession-
about 50 mph, the larger the speed of the accident-involved vehicles, the less is their involvement rate. This is the opposite of what the stopping distance conjecture suggests. Only the right branch of the U-shaped curve could support the conjecture that the probability of accident occurrence increases with speed.

In the same study Solomon shows (Figure 4) that accident severity increases with speed. Thus, at least a part of the increasing tendency of the right branch of the curve in Figure 3 reflects that the higher the speed, the larger is the proportion of accidents that are reportable and get reported.

How much of the increasing tendency of the right branch of the curve in Figure 3 is due to the increased probability of accident occurrence and how much is due to increased accident severity cannot be said. To explain why, consider the invented example of Table 1.

The story line is that at the end of the “before” period there was an increase in the speed limit, causing a shift in the speed distribution. One can see in the unshaded numbers of Table 1 a before-to-after increase in the number of reported crashes for each severity class. In inventing these numbers, it was assumed that after the speed limit change, the number of crashes did not change; only some crashes got more severe and this caused a transfer of 1% of the crashes to the adjacent higher severity category. Thus, if in the before period there were 50,000 crashes that were not severe enough and did not get reported, then 500 would be shifted into the property damage only.
(PDO) column in the after period. At the same time, 60 (1% of 6,000) of the PDO crashes would be transferred into the Nonfatal Injury column and so forth. The upshot is that what appears to be an increase in crash frequency could come about entirely as a result of increases in severity and without any increase in the probability of crashes to occur. The general issue of frequency–severity indeterminacy and its repercussions is described in Hauer (7).

The left branch of Figure 3 also suffers from critical shortcomings. Foremost is the fact that many of the slow-vehicle accidents in Solomon’s data involved turning vehicles. Therefore what appears to be due to low speed may be partly due to the maneuver that necessitated it. This question was later explored in a study by the Research Triangle Institute (RTI) that found that 44% of accidents and 56% of accident involvements “had at least one vehicle directly involved in some turning maneuver or was directly influenced by another vehicle . . . involved in some turning maneuver” (8, p. 18). The impact of excluding such involvements from the analysis is shown in Figure 5.

Another problem affecting both the left and the right branches of the U-shaped curve stems from a subtle statistical artifact. From the kind of data assembled by Solomon (6), RTI (8), and Kloeden et al. (9), one would tend to find a U-shaped curve even if speed had nothing to do with the probability of being in a crash. For example, each data point in Figure 3 and Figure 5 represents the ratio: (proportion of vehicles with speed \( V \) in crashes)/(proportion of vehicles with speed \( V \) on the road). The speed in the denominator is measured fairly accurately; the speed in the numerator is less accurately determined because it comes from estimates by police, the crash-involved drivers, or accident reconstruction. Therefore, even if the two true speed distributions were equal (i.e., if the probability of a crash for all speeds were the same), the distribution of estimated \( V \) in the numerator would be wider than that in the denominator. To visualize the consequences of the two kinds of speeds being measured with differing accuracies, assume that the speeds on the road are normally distributed with a mean of 60 mph and a standard deviation of 3 mph and that the pre-crash speeds of crash-involved vehicles have the same distribution. Assume further that the process of precrash speed estimation for crash-involved vehicles adds some uncertainty and therefore the estimates of their precrash speeds are normally distributed with the same mean (60 mph) but a slightly larger standard deviation of 4 mph. Dividing the ordinates of the wider normal probability density by the narrower one shows that Solomon’s procedure is expected to yield a curve like that in Figure 6, even though it should be a horizontal line. A fuller explanation is provided by Hauer (10). That Solomon’s curve is partly a statistical artifact was recognized and forcefully stated in 1970 by White and Nelson (11). However, in 2003 Solomon’s results were still being used as an argument against differential speed limits for trucks and cars (12).

To explain his surprising results, Solomon showed his data in another way. Instead of travel speed on the horizontal axis of Figure 3, he subtracted the mean speed, making the horizontal axis into variation (deviation) from mean speed. This led to his interpretation that it is not speed that affects the probability of accident involvement but that “the greater the variation in speed of any vehicle from the average speed of all traffic, the greater its chance of being involved in an accident” (5, p. 1). Inasmuch as this amounts to just a shift of the horizontal axis, this interpretation suffers from all the shortcomings and uncertainties already discussed.

Attempts to replicate Solomon’s U curve were not successful. Munden (13) found that drivers observed once during his study did not yield a U-shaped curve. Drivers driving habitually at less than or more than the average speed did show a mild U-shaped curve. There

### TABLE 1  Crashes Before and After Change in Speed Limit

<table>
<thead>
<tr>
<th></th>
<th>Not in Official Records</th>
<th>In Official Records</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unreported Crashes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Property Damage Only</td>
<td>6,000</td>
<td>4,000</td>
</tr>
<tr>
<td>Nonfatal Injury</td>
<td>4,020</td>
<td>80</td>
</tr>
<tr>
<td>Fatal Injury</td>
<td>80</td>
<td></td>
</tr>
</tbody>
</table>

Before 50,000 6,000 4,000 40
After 49,500 6,440 4,020 80

FIGURE 5 Impact of excluding involvements, based on Tables 3.1.1 and 3.1.3 from Research Triangle Institute project (8).
Event Phase: How Accident Severity Depends on Speed

Damage to vehicle and to occupant depends on pressure, deceleration, change in velocity, and the kinetic energy dissipated by deformation. All of these are increasing functions of precrash velocity. What is predicted by Newtonian physics is amply supported by data. Figure 7 shows the results of a 10-year study of crashes for restrained front-seat occupants.

In this figure injury severity on the vertical axis is represented by MAIS, the maximum Abbreviated Injury Scale (AIS) scores of six body regions. The AIS represents the “threat to life” associated with an injury. The horizontal axis is $\Delta v$, “the change in velocity of a vehicle’s occupant compartment during the collision phase of a motor vehicle crash” (16). Figure 7 shows that the proportion of occupants sustaining a moderate or more severe injury increases with $\Delta v$. Thus, for example, in a crash in which $\Delta v$ is 30 to 34 km/h, about 40% of female restrained front-seat occupants will sustain an injury for which MAIS $\geq 2$, but when $\Delta v$ is in the 50 to 55 km/h range, about 75% sustain such injury.

Using National Accident Sampling System data about passenger cars involved in accidents from 1980 through 1986, Joksch (17) found that the probability of the driver being killed in a reported motor vehicle accident was $(\Delta v/70.6)^{\alpha}$. The NHTSA (18) provides equations to calculate the risk of injury to equal or exceed all six MAIS injury levels. Thus, for example, for MAIS = 6 (unsurvivable injury), the probability of a passenger vehicle occupant to die is $e^{0.1525\Delta v - 8.2629}/(1 + e^{0.1525\Delta v - 8.2629})$. The models by Joksch and the NHTSA give similar results. The conclusion is inescapable; the severity of injury and the chance of dying increase dramatically with $\Delta v$.

How Safety Changes When Mean Speed Changes

The main question is, how does the number of accidents, by severity, depend on the distribution of speeds? For some reason most of past research is not about this question but about $(a)$ how the probability of accidents depends on speed and $(b)$ how the severity of outcome once an accident has occurred depends on speed. The hope was that the answer to the main question would emerge from answering questions $a$ and $b$. However, for reasons already explained, there is no consensus on the answer to question $a$. In addition, while it is clear that severity increases with speed, it is not easy to estimate $\Delta v$ or to know how it depends on the distribution of speeds; $\Delta v$ depends not only on the precrash speed of one vehicle but also on the speed and direction of the other vehicle(s) in the crash, on their relative masses, and on other factors. In short, based on the information in the earlier sections, the main question of interest cannot be answered.

Some researchers did not succumb to the analyze-first-and-synthesize-later habit and strove to answer the question of interest directly. Using results from several studies in which mean speed changed from before to after, Nilsson (19) found that if the mean speed of a road changed from $\bar{v}_i$ to $\bar{v}_j$, the ratio of accidents $(N_i/N_j)$ of a given severity was proportional to the ratio $(\bar{v}_j/\bar{v}_i)^\alpha$ with $\alpha = 4$ for fatal accidents, $\alpha = 3$ for fatal plus serious injury accidents, and $\alpha = 2$ for all injury accidents. This “power model” was later refined in Nilsson’s doctoral dissertation (20). Elvik et al. (21) assembled...
a large data set from 97 published studies containing 460 results about \( \bar{v}_0, \bar{v}, N_0, \) and \( N_f \). Their data about fatal accidents are shown in Figure 8.

Each point in the figure is one study result. Most results are in the “expected” regions. That is, when the mean speed increased, so did the number of fatal accidents and vice versa. Similar results were obtained for injury accidents. Elvik et al. (21) also used Nilsson’s power model and their estimates of \( \alpha \) are listed in Table 2.

The power model implies, for example, that a 3-mph reduction from a mean speed of 30 mph will cause the same reduction in the proportion of crashes as a 6-mph reduction from a mean speed of 60 mph. Because this implication was thought to be counterintuitive by some, Hauer and Bonneson (22) were asked to examine whether the data prepared and used by Elvik et al. provide empirical support for the power model.

The relationships in Figure 8 can be represented by the separable differential equation

\[
\frac{dN}{N} = \alpha f(\bar{v}) d\bar{v}
\]

the solution of which depends on what \( f(\bar{v}) \) is. Thus, if \( f(\bar{v}) \) is constant, then

\[
N = N_0 e^{\alpha(\bar{v}-\bar{v}_0)}
\]

if \( f(\bar{v}) \) equals \( \frac{1}{\bar{v}} \), then

\[
N = N_0 \left( \frac{\bar{v}}{\bar{v}_0} \right)^\alpha
\]

and so forth. It follows that the power model is the right choice if the data indicate that \( f(\bar{v}) \) equals \( \frac{1}{\bar{v}} \). Whether this is true can be examined by plotting \( (1/N_0) (dN/d\bar{v}) \) against \( \bar{v}_0 \). No such dependence was found, certainly not one indicating that \( f(\bar{v}) \) is halved for a doubling of \( \bar{v} \), as implied by the power model. The plots were completely flat and the most that could be assumed is that \( f(\bar{v}) \) might change linearly with \( \bar{v} \). For this reason, \( f(\bar{v}) = 1 + \beta \bar{v} \) was chosen.

The parameters \( \alpha \) and \( \beta \) were estimated by weighted least-squares such that the weight of each study result takes into account both the number of accidents and the method used. Their estimates for two alternative models (A and B) when \( d\bar{v} \) is measured in mph are listed in Table 3. If \( d\bar{v} \) is measured in km/h, multiply \( \alpha \) and \( \beta \) by 1.609.

These parameters are to be used in differential relationships:

\[
dN = \alpha N (1 + \beta \bar{v}) d\bar{v}
\]

and

\[
AMF = \frac{N + dN}{N} = 1 + \alpha (1 + \beta \bar{v}) d\bar{v}
\]

where AMF is the accident modification function. To illustrate the application of these equations, consider the following numerical example: A measure is expected to reduce the mean speed by 1.2 mph. The mean speed “before” was 60 mph and the number of fatal accidents was 500. The task is to compute \( dN \) and AMF for fatal accidents.

1. Compute \( dN \). Model A predicts \( dN = 0.1046 \times 500 \times (-1.2) = -62.8 \) fatal accidents. Model B predicts \( dN = 0.2666 \times 500 \times (1 - 0.0098 \times 60) \times (-1.2) = -65.9 \) fatal accidents. For fatal accidents the power model uses \( \alpha = 3.6 \) from Table 2 and predicts

\[
\left( \frac{N + dN}{N} \right) = \left( \frac{58.8}{60} \right)^{3.6} = 0.93
\]

or \( dN = 500 \times (0.93 - 1) = -35 \). The power model estimates, in this circumstance, a substantially smaller reduction in fatal accidents.

2. Compute AMF. Model A predicts AMF = 1 + 0.1046 \times (-1.2) = 0.874. Model B predicts AMF = 1 + 0.2666 \times (1 - 0.0098 \times 60) \times (-1.2) = 0.868. The power model predicts 0.93.

### Table 2: Estimates of \( \alpha \) Elvik et al.

<table>
<thead>
<tr>
<th>Severity</th>
<th>Estimate of ( \alpha )</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fatalities</td>
<td>4.5</td>
<td>4.1–4.9</td>
</tr>
<tr>
<td>Seriously injured road users</td>
<td>2.4</td>
<td>1.6–3.2</td>
</tr>
<tr>
<td>Slightly injured road users</td>
<td>1.5</td>
<td>1.0–2.0</td>
</tr>
<tr>
<td>All injured road users (including fatally)</td>
<td>1.9</td>
<td>1.0–2.8</td>
</tr>
<tr>
<td>Fatal accidents</td>
<td>3.6</td>
<td>2.4–4.8</td>
</tr>
<tr>
<td>Serious injury accidents</td>
<td>2.0</td>
<td>0.7–3.3</td>
</tr>
<tr>
<td>Slight injury accidents</td>
<td>1.1</td>
<td>0.0–2.4</td>
</tr>
<tr>
<td>All injury accidents (including fatal)</td>
<td>1.5</td>
<td>0.8–2.2</td>
</tr>
<tr>
<td>PDO accidents</td>
<td>1.0</td>
<td>0.0–2.0</td>
</tr>
</tbody>
</table>

### Table 3: Estimated Parameters When \( d\bar{v} \) Is in mph

<table>
<thead>
<tr>
<th></th>
<th>( \hat{\alpha} )</th>
<th>( \hat{\beta} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fatal accidents</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>0.1046</td>
<td>Set to 0</td>
</tr>
<tr>
<td>B</td>
<td>0.2666</td>
<td>-0.0098</td>
</tr>
<tr>
<td>Nonfatal injury accidents</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>0.0670</td>
<td>Set to 0</td>
</tr>
<tr>
<td>B</td>
<td>0.0838</td>
<td>-0.0051</td>
</tr>
</tbody>
</table>
As is obvious from Figure 8, there is considerable noise in the data. This noise reflects in part the randomness of accident counts, in part the variety of circumstances under which the data were obtained, and in part the variety of causes of change in mean speed. The question of whether these results would apply regardless of the cause of the change in mean speed cannot be well answered at this time. If the observed change in the number of accidents reflects mainly the associated change in severity, then the results may apply generally.

In the numerical example, the introduction of some measure was expected to reduce the mean speed by 1.2 mph. Although all computations depend on this expected $\Delta v$, it was not made clear where such an expectation originates. The most common measure by which speed is influenced is a change in the posted speed limit. The relationship between changes in posted speed limit was examined by Elvik et al. (21). They found that, on the average, “the change in the mean speed of traffic induced by a change in speed limit appears to be around 25% of the change in speed limit” (21, p. 90). This probably varies by setting. Thus, for example, in rural settings, the change in mean speed was found to be, on average, 42% of the change in speed limit.

### SUMMARY

Two questions have been discussed: “How does what professionals do affect the evolution of speeds?” and “How does speed affect safety?” That more was said about the second question than about the first does not reflect their relative importance. It reflects only the amount of attention they received in research. Clearly one cannot anticipate how safety is affected by what we do without answering both questions.

The discussion of the first question is anecdotal and speculative in tone. This paper has shown how speed has evolved over time in one specific case. This allowed the author to ask, If it evolves, what drives the change? The question could be answered only in generalities: perhaps it is the smoother ride, the wider lanes, more travel on freeways, and so forth. There might even be mechanisms that would drive an upward drift in speed. But speculation is of little use. The extent and universality of the speed drift are not even known. What is missing is knowledge of fact.

Similar to the question of how speed evolves over time is the question of how it spreads over distance (space). It has been established that there is some speed inertia, a carryover from a faster to a slower road. However, it is not well known how this decays with distance and, more importantly, whether and to what extent the increase in speed on one set of roads spills over to other, more distant roads.

Three questions were addressed more extensively: (a) How does the probability of accident involvement depend on speed?, (b) How does the severity of the outcome depend on speed?, and (c) How does safety change when the mean speed changes? On the first question there are strong beliefs supported by weak evidence. To many it seems obvious that the faster one drives the more likely one is to crash. This is why the dependence of the stopping distance on speed plays such an important role in geometric design. Others believe that the likelihood of a crash has more to do with deviation from mean speed. The paper explains why what seems obvious is not easy to demonstrate. First, the early research did not distinguish between slow and turning vehicles. Second, from the kind of data used one cannot possibly know whether the observed differences in relative accident rate are due to probability of accident involvement or due to severity of outcome. Third, past studies neglected to account for the fact that the speed on the road and the speed in a crash are estimated to a different accuracy. The result is that the relative rate presents itself in the form of a U-shaped curve, even when in reality it is a straight horizontal line. In short, all can still believe what they choose; at this point the answers from research are inadequate.

The question of how severity depends on speed can be answered with clarity. The mechanism of damage to vehicle and occupant is well understood; it is clear that damage increases with precrash velocity, and what physics predict is amply supported by data. As a result, one can show how the probability of being killed or sustaining an injury of a given severity in an accident increases as a function of the change in velocity. That is, if one can estimate $\Delta v$, the change in velocity of the passenger compartment at the time of the crash, it is possible to associate with it a probability of injury of any given severity.

The hope may have been that, by establishing (a) how the probability of accident involvement depends on speed and (b) how accident severity depends on speed, one could answer the question of interest: How does the number of accidents by severity depend on speed? This hope turned out to be vain for two reasons. First, the answer to question (a) is not clear. Second, outcome severity depends not on speed but on the change in speed $\Delta v$; which, in turn, depends on many factors, not only the speed of the crashing vehicle. Therefore, the question of interest had to be answered directly.

There are many research studies about the safety effect of countermeasures that changed the mean speed on roads. Summarizing their results, Nilsson (19, 20) and Elvik et al. (21) suggested using the power model. The implications of the power model are somewhat counterintuitive and, on closer examination, are not in accord with their data. Hauer and Bonneson used Elvik’s data to estimate a different model (22), one that is largely free of counterintuitive implications. The results are presented in Equations 1 and 2 and in Table 3.

In conclusion, there can be no reasonable doubt that if speed increases while other conditions (vehicles, roads, medical services) remain unchanged, accidents will be more severe and therefore more accidents will be reported. Given a change in mean speed, one can predict the consequences in injuries and fatalities. The link between what we do (by vehicle design, advertising, speed limits, infrastructure standards, etc.) and the speeds on the road is less clear. We know that speeds evolve over time but do not know exactly why. We know that there is some spillover of the change from one road to another but cannot well predict its size or extent.

### REFERENCES


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