A Risk-Based Method for Modeling Traffic Fatalities

Kavi Bhalla,1∗ Majid Ezzati,2 Ajay Mahal,2 Joshua Salomon,2 and Michael Reich2

We describe a risk-based analytical framework for estimating traffic fatalities that combines the probability of a crash and the probability of fatality in the event of a crash. As an illustrative application, we use the methodology to explore the role of vehicle mix and vehicle prevalence on long-run fatality trends for a range of transportation growth scenarios that may be relevant to developing societies. We assume crash rates between different road users are proportional to their roadway use and estimate case fatality ratios (CFRs) for the different vehicle-vehicle and vehicle-pedestrian combinations. We find that in the absence of road safety interventions, the historical trend of initially rising and then falling fatalities observed in industrialized nations occurred only if motorization was through car ownership. In all other cases studied (scenarios dominated by scooter use, bus use, and mixed use), traffic fatalities rose monotonically. Fatalities per vehicle had a falling trend similar to that observed in historical data from industrialized nations. Regional adaptations of the model validated with local data can be used to evaluate the impacts of transportation planning and safety interventions, such as helmets, seat belts, and enforcement of traffic laws, on traffic fatalities.

KEY WORDS: Developing countries; global health; motor vehicles; road traffic injuries; traffic safety; transportation growth

1. BACKGROUND

Road traffic injuries and fatalities account for 1.2 million deaths worldwide (2.2% of global mortality in the year 2002) and 2.6% of the total global burden of disease, measured in terms of lost years of healthy life. Recent projections have estimated that as income and vehicle ownership levels rise in the developing world, the global number of road traffic deaths would increase by approximately two-thirds by the year 2020.

The link between traffic deaths and the size of vehicle fleet was first explored by Smeed in 1949 using traffic fatality and registered vehicle statistics from 20 industrialized countries over the time period 1930–1946. This analysis showed that fatalities per vehicle decreased monotonically with vehicle ownership (i.e., vehicles per person) while fatalities per capita increased over this period. Since the late 1960s, however, fatalities per capita have fallen for most industrialized nations. Soderlund and Zwi used multiple regression analysis of cross-sectional data on road traffic deaths in 1990 from 83 countries to describe fatalities per vehicle and per capita as a function of vehicle ownership levels, road density, income, health expenditure, and population density. The analysis showed that traffic fatalities increased with income at low incomes but fell at higher incomes. Fatalities per vehicle always fell. Using panel data from 1963–1999 for 88 countries, Kopits and Cropper developed an econometric model that related traffic fatalities to income growth and vehicle ownership. The authors used this model to project worldwide traffic fatalities to the year 2020. Since the historical fatality trends in the industrialized world did

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not reverse until their per capita income levels were above $8,000 (1985 international dollars), these models predicted a large increase in traffic fatalities for developing countries, which have significantly lower income levels at present.

Such econometric projections are valuable because they provide visions of future public health burden imposed by traffic injuries and fatalities. Projections based on historical data, however, do not predict the effects of unprecedented changes in the transportation system. For instance, the regression equations derived in Smeed(4) accurately predicted traffic fatalities in the United Kingdom up to the mid 1960s, when the traffic fatalities peaked. If these relationships were extrapolated to current times, however, they would predict about four times the actual traffic fatalities in the year 2000. The deviations from a rising trend in fatalities are often attributed to the introduction of road safety programs. Road traffic fatalities may also be influenced by other systemic changes. For example, rapid motorization in cities in many developing countries has led to traffic congestion and lower vehicle speeds, which could cause a reduction in road fatalities, albeit with other health and welfare consequences such as air pollution exposure or psychological stress. Similarly, many developing nations have a vehicle mix (e.g., widespread reliance on scooters) that has not been observed in the historical data from industrialized nations. Since many of these characteristics of the transportation sector are unique to developing countries, econometric models of traffic injuries that rely on historical data from industrialized countries can result in highly uncertain or biased predictions.

In contrast to aggregate econometric analysis of observed trends, structural models that simulate the dynamic response of the transportation system can be used to study the impact of a range of variables that affect traffic fatality rates. In this article, we develop a risk-based model for the relationship between transport mode, vehicle mix, and traffic fatalities. This is accomplished by combining the probability of a crash between different road users and the probability of a fatality in the event of a crash. An advantage of this model is that alternative scenarios of vehicle ownership and use—which may be based on income, vehicle prices, and policy choices—can be systematically analyzed. We illustrate this by using the model to simulate the safety consequences that result from four scenarios of transportation growth. Three of the scenarios emphasize specific transportation modes (high bus use, high car use, high scooter use), and the fourth represents a mixed-use base case scenario. Beyond the illustrative application in this article, validated regional adaptations of the model can be used to evaluate the impacts of transportation planning and safety interventions, such as helmets, seat belts, and enforcement of traffic laws, on traffic fatalities in a common framework.

We start with a crude model that assumes that cars are the only mode of motorized transport available in a society. We find broad similarities in trends with historical data even with the simple model representation. Next, we extend the model to include other vehicle types and consider pairwise fatality risks derived from a review of the vehicle safety literature.

2. CRUDE MODEL: CARS AND PEDESTRIANS

First consider a simple model in which walking and cars are the only available modes of transportation. We assume that the probability of fatality in the event of a crash is $r$ for a pedestrian and negligible for a car occupant. If there is a commuting population of $N$, of which $C$ are car users and the remaining are pedestrians, the probability of a pedestrian-car crash is proportional to both the number of pedestrians as well as the number of cars, $C(N - C)$, and the probability of a car-car crash is proportional to $C$. Thus, if we set the fatality risk in car-car crashes to $0$, the per capita fatality risk is proportional to $C(N - C)r/\bar{N}$, which is a parabolic function of the number of cars. As the society motorizes from all-pedestrians to all-occupants (Fig. 1), the aggregate fatality risk initially rises as additional cars pose an increasing threat to the largely pedestrian population. But, when more than half the commuting population consists of car users ($C = 0.5$, peak of parabola), increasing motorization leads to a fall in the aggregate fatality risk. On the other hand, the aggregate risk per car, $(N - C)r$, is a linearly decreasing function of the number of cars. The results of this simple model show patterns that are qualitatively similar to the panel data reported by Kopits and Cropper(3) (Figs. 2A and 2B). Fatalities per vehicle always fall with increasing motorization, while fatalities per capita initially increase with vehicle ownership and then fall, showing the inverted-U relationship that has been observed in past studies(3,6) These results are the consequence of a “substitution effect,” where high-risk and low-threat pedestrians are replaced by low-risk and high-threat vehicles. Thus, the people who shift from being vulnerable road users (VRUs) to vehicle occupants...
Fig. 1. Motorization and changing traffic risk in a world with only cars and pedestrians. \( r \) is the threat to each pedestrian per car, while the risk to car occupants is assumed to be negligible in comparison.

Fig. 2. A comparison of historic panel data (1963–1999, 88 countries reported by Kopits and Cropper, 2005) for fatalities per person, (A), and fatalities per vehicle, (B), with predictions of the simple model, (C) and (D).
diminish their own risks but raise the threat to the remaining VRUs. At low levels of motorization, there are a large number of VRUs on the streets and the increased threat to the population outweighs the decreased risk to the individual. However, at high motorization levels there are relatively few VRUs, and the decreased personal risk leads to a falling trend in fatalities per capita even in the absence of traffic safety interventions. Similarly, the aggregate population-level risk per vehicle is proportional to the number of at-risk people. Since each additional car in this crude model implies one fewer pedestrian, the at-risk population falls monotonically, resulting in falling fatalities per vehicle.

3. MULTIVEHICLE MODEL FORMULATION

Next, we expand the analysis to include other modes of transportation that are commonly observed in developing countries. The probability of a fatal crash between two road users can be modeled as the product of the probability that a crash occurs between the road users and the probability that the crash is fatal. Thus, if $c^{\text{threat}}_{\text{victim}}$ is the probability that a road user (victim) is struck by a vehicle (threat), and $r^{\text{threat}}_{\text{victim}}$ is the case fatality ratio (CFR) for the victim of the crash, then the probability that the victim is killed is given by

$$c^{\text{threat}}_{\text{victim}} = c^{\text{threat}}_{\text{victim}} \times r^{\text{threat}}_{\text{victim}}.$$  \hspace{1cm} (1)

We use the superscript to denote the transportation mode of the threat and subscript to denote the transportation mode of the victim. Thus, for instance, $r^{\text{car}}_{\text{environment}}$ is the probability that a scooter-rider is killed in the event of a car-scooter crash, while $r^{\text{scooter}}_{\text{car}}$ is the probability that the car occupant is killed. Single-vehicle crashes are incorporated by including the physical environment as a threat. Thus, for instance, $r^{\text{scooter}}_{\text{scooter}}$ is the probability that a single-vehicle scooter crash is fatal. In this formulation, we assume that a crash can involve at most two vehicle types (in the United States 15% of fatal car crashes involve more than two vehicles). \(^7\) Mathematical formulation of crashes involving multiple vehicles is analogous to the model presented here.

3.1. The Probability of a Crash Event, $c^{\text{threat}}_{\text{victim}}$

For each pair of transportation modes, the probability of a crash between the threat and the victim depends on a number of factors that include:

1. The population of road users that belong to the victim's travel mode, $U_{\text{victim}}$, and the number of "at-risk" miles traveled (i.e., distance over which the victim is exposed to the threat) by each of these road users, $d_{\text{victim}}$;
2. The total number of threat vehicles, $M_{\text{threat}}$, and the number of miles traveled by each of these vehicles, $d_{\text{threat}}$;
3. Vehicle attributes (e.g., antilock brakes, visibility, stability);
4. Driver attributes (e.g., sociodemographic characteristics, license status, alcohol use, driver training);
5. Roadway infrastructure (pedestrian walkways, lane separating medians); and
6. Broader systemic attributes (legal and insurance systems);

that is,

$$c^{\text{threat}}_{\text{victim}} = f(U_{\text{victim}} \times d_{\text{victim}}, M_{\text{threat}} \times d_{\text{threat}}; \text{vehicle attributes, driver attributes, roadway attributes, systemic attributes}).$$

We consider a specific form for this relationship

$$c^{\text{threat}}_{\text{victim}} = K^{\text{threat}}_{\text{victim}} \times U_{\text{victim}} \times d_{\text{victim}} \times M_{\text{threat}} \times d_{\text{threat}}.$$  \hspace{1cm} (2)

As written, the probability of a specific threat-victim crash is proportional to the product of the total "at-risk" miles traveled by road users in the victim's travel mode ($U_{\text{victim}} \times d_{\text{victim}}$) and the total distance traveled by the vehicles that pose the threat ($M_{\text{threat}} \times d_{\text{threat}}$). The proportionality constant, $K^{\text{threat}}_{\text{victim}}$, accounts for all the other variables listed in items 3–6 above and captures the relationship between road use and the probability of a crash. Thus, for car-pedestrian crashes, $U_{\text{pedestrian}} \times d_{\text{pedestrian}}$ is the number of at-risk miles walked by all pedestrians, $M_{\text{car}} \times d_{\text{car}}$ is the total number of miles traveled by all cars, and $K^{\text{car}}_{\text{pedestrian}}$ is a proportionality constant that relates the rate at which shared roadway use results in pedestrian-vehicle crashes. Since the variables $M_{\text{threat}}$ and $d_{\text{threat}}$ do not have a physical interpretation for single-vehicle crashes, we assume that $c^{\text{environment}}_{\text{victim}} = K^{\text{environment}}_{\text{victim}} \times U_{\text{victim}} \times d_{\text{victim}}$, so that the proportionality constant $K^{\text{environment}}_{\text{victim}}$ relates vehicle use to the probability of a single-vehicle crash.
3.2. The Case Fatality Ratio, $r_{\text{threat} \times \text{victim}}$

The CFR, the probability of fatality in the event of a crash, depends on precrash variables that describe the characteristics of vehicles and victims, the crash variables, and the postcrash victim care. These include:

- Vehicle characteristics (e.g., size, mass, and shape) and safety design technology (e.g., availability and use of seat belts and airbags);
- Victim attributes including age, sex, height, and weight;
- Crash conditions including vehicle speed, direction of vehicle travel, crash avoidance maneuvers, weather conditions, and roadway infrastructure; and
- Postcrash medical care including response time of emergency medical services, and quality of on-site and trauma care;

that is,

$$r_{\text{threat} \times \text{victim}} = f(\text{vehicle attributes, victim attributes, crash conditions, post crash medical care}).$$

3.3. Computing Traffic Fatalities

Combining Equations (1) and (2),

$$\text{fatal}_{\text{threat} \times \text{victim}} = K_{\text{victim}} \times U_{\text{victim}} \times d_{\text{victim}} \times M_{\text{threat}} \\
\times d_{\text{threat}} \times r_{\text{threat} \times \text{victim}}. \quad (3)$$

Vehicle occupancy relates the number of vehicles to the number of occupants. Thus, $U_{\text{victim}} = o_{\text{victim}} \times M_{\text{victim}}$, where $o_{\text{victim}}$ is the vehicle occupancy of the victim’s transport mode. If $D_{\text{victim}} = U_{\text{victim}} \times d_{\text{victim}}$ is the total at-risk vehicle distance traveled by road users of the victim’s transport mode, and $D_{\text{threat}} = M_{\text{threat}} \times d_{\text{threat}}$ is the total distance traveled by threat vehicles, we get:

$$\text{fatal}_{\text{threat} \times \text{victim}} = K_{\text{victim}} \times o_{\text{victim}} \times D_{\text{threat}} \times D_{\text{victim}} \\
\times d_{\text{threat}} \times r_{\text{threat} \times \text{victim}}. \quad (4)$$

Total fatalities among road users in a particular mode of transportation can be computed by adding the fatality contributions from all threats. Thus, for instance, $\sum_{\text{threat}} \sum_{\text{victim}} \text{fatal}_{\text{threat} \times \text{victim}}$ computes all car-occupant fatalities. Similarly, $\sum_{\text{victim}} \text{fatal}_{\text{threat} \times \text{victim}}$ is the total fatalities caused by cars among other road users. The aggregate traffic fatalities (all victims from all threats) are then $\sum_{\text{threat}} \sum_{\text{victim}} \text{fatal}_{\text{threat} \times \text{victim}}$.

4. MODEL APPLICATION

As an illustrative application of the methodology, we use the model (Equation 4) to analyze the role of vehicle mix and vehicle prevalence on long-run fatality trends. This requires the following simplifying assumptions (see discussion for the implications of these assumptions):

- $K_{\text{victim}}$ and $r_{\text{victim}}$ are held constant in order to analyze the role of vehicle mix and vehicle prevalence on crash fatalities. In future studies, changes in crash risk and CFR due to changes in infrastructure (e.g., divided roads), vehicle design and use (e.g., seatbelts and airbags), and other systemic changes (e.g., enforcement of speed limits and emergency services for crash victims) can be modeled by using time dependent values for $K$ and $r$.

4.1. Computing Pairwise CFRs, $r_{\text{threat} \times \text{victim}}$

The pairwise CFRs, $r_{\text{threat} \times \text{victim}}$, can be represented as a matrix with the threats listed in columns and the victims listed in rows. The CFR matrix was populated in a sequence of 13 steps described in Table I. Wherever possible, we assume that the pairwise CFRs, $r_{\text{threat} \times \text{victim}}$, correspond to a head-on crash at a mean speed of 30 km/h. We rely primarily on U.S.-based studies and data available from the National Highway Traffic Safety Administration (NHTSA). The CFR matrix, $r_{\text{threat} \times \text{victim}}$, developed as described in Table I, is shown in Table II. Clearly, these pairwise risks evolve with changes in technology and infrastructure. However, they are held constant in this application in order to
Table I. Steps in Constructing the CFR Matrix

<table>
<thead>
<tr>
<th>Threat</th>
<th>Pedestrian</th>
<th>Scooter</th>
<th>Car</th>
<th>Bus</th>
<th>Environment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scooter</td>
<td>[13]</td>
<td>[12]</td>
<td>[7]</td>
<td>[7]</td>
<td>[10]</td>
</tr>
<tr>
<td>Car</td>
<td>[1]</td>
<td>[8]</td>
<td>[5]</td>
<td>[6]</td>
<td>[10]</td>
</tr>
<tr>
<td>Environment</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>

1. Pedestrians pose no threat to other pedestrians and to occupants of cars and buses.
2. Pedestrians are at no risk from the environment, that is, injuries from falls are not modeled.
3. **Car-Pedestrian:** Based on Anderson, the probability of a pedestrian fatality in the event of a car-pedestrian crash is 0.08.
4. **Bus-Pedestrian:** The CFR in a bus-pedestrian crash is higher than that in a car-pedestrian crash because of the difference in vehicle shape and mass. Leffler and Gabler compared the injury risk to pedestrians from light trucks and vans (LTVs) in the United States. They found that at speeds in the range of 21–30 km/h, the probability of serious head injury due to an LTV is 9.1% higher than when impacted by a car. However, the probability of a serious chest injury was 128% higher. Since both head and chest injuries are a common cause of pedestrian fatalities, we assume that the pedestrian fatality risk from LTVs is the average of these two estimates (i.e., the CFR is 68.5% higher than that from cars and is set at 0.135). Since the population of LTVs in the United States largely consists of sport utility vehicles and passenger vans, the mass of the vehicles studied by Leffler and Gabler is significantly lower than that of a bus. Thus, while their analysis captures the increased threat posed by flat-front vehicles, the study does not account for the effect of increased vehicle mass. However, since LTVs and buses are both much heavier than a pedestrian, we assume vehicle mass can be ignored as an additional risk factor in vehicle-pedestrian crashes.
5. **Car-Car and Bus-Bus:** Joksch analyzed the National Accident Sampling System, which provides representative data on vehicle crashes in the United States. They found that the CFR for driver fatalities was proportional to the fourth power of the vehicle velocity. Using their formula, we set the CFR for occupants in car-car and bus-bus collisions to 0.009.
6. **Bus-Car and Car-Bus:** In the event of a crash between vehicles of different masses, we assume that the probability of fatality in the impacted vehicle is proportional to the mass ratio of the two vehicles involved. This is reasonable because the kinetic energy of each vehicle is linearly related with their mass. We assume that the mass of a typical bus is about eight times that of a car. Thus, since the CFR in a car-car crash is 0.009, the CFR for the car occupant in a car-bus collision is eight times greater, 0.072, and that for a bus occupant is eight times smaller, 0.001 (rounded to three significant digits). The validity of this calculation can be verified by comparing with the fatality outcome in car-truck impacts in the United States. According to the National Highway Traffic Safety Administration (NHTSA), in car-truck crashes the car occupant was 63 times more likely to be killed than the truck occupant. Our analysis suggests that this ratio is 64. However, it should be noted that trucks in the United States may be much heavier than a typical bus in a developing country.
7. **Car-Scooter and Bus-Scooter:** We assume that the threat posed by vehicles to scooter-riders is the same as that to pedestrians (i.e., 0.08 for car-scooter and 0.135 for bus-scooter). It should be noted that this risk is a strong function of helmet use. Thus, in the absence of a helmet the CFR for a scooter rider may be much higher than that for a pedestrian because of the higher relative impact speed. However, in the presence of a helmet, the CFR may be significantly lower.
8. **Scooter-Car:** Based on motorcycle-car crashes in the United States reported by NHTSA, the motorcyclist is 44 times more likely to be killed than the car occupant. Since this number is closely related with helmet-use rates, it should be noted that helmet use is relatively low in the United States—most states do not have universal motorcycle helmet laws, and in the absence of such laws helmet use is approximately 50%. Thus, if we assume that scooters behave similar to motorcycles in crashes, the CFR for car occupants in crashes with scooters is 1/44 of 0.08 (≈0.002).
9. **Scooter-Bus:** We assume that scooters do not pose any threat to bus occupants.
10. **Single-vehicle crashes:** Based on data for the United States, the ratio of fatal single-vehicle crashes to those that resulted in injuries is 0.053, 0.030, and 0.037 for motorcycle, car, and truck crashes, respectively.
11. **Scooter-Pedestrian:** The pedestrian CFR in scooter-pedestrian crashes is half the pedestrian CFR in car-pedestrian crashes in New Delhi. Thus, the pedestrian CFR in scooter-pedestrian crashes is half of 0.04 (≈0.02).
12. **Scooter-Scooter:** The CFR in scooter-scooter crashes in New Delhi was 26% of the CFR in car-car crashes (i.e., 0.021).
13. **Pedestrian-Scooter:** In the absence of any crash data on the threat to scooter riders from pedestrians, we assume that this risk is half that of the CFR in scooter-scooter crashes.
Table II. Case Fatality Ratio Matrix, $\frac{\text{threat}}{\text{victim}}$

<table>
<thead>
<tr>
<th>Threat</th>
<th>Pedestrian</th>
<th>Scooter</th>
<th>Car</th>
<th>Bus</th>
<th>Environment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pedestrian</td>
<td>0$^{[1]}$</td>
<td>0.040$^{[1]}$</td>
<td>0.080$^{[3]}$</td>
<td>0.135$^{[4]}$</td>
<td>0$^{[2]}$</td>
</tr>
<tr>
<td>Scooter</td>
<td>0.010$^{[1]}$</td>
<td>0.021$^{[12]}$</td>
<td>0.080$^{[7]}$</td>
<td>0.135$^{[7]}$</td>
<td>0.053$^{[10]}$</td>
</tr>
<tr>
<td>Car</td>
<td>0$^{[1]}$</td>
<td>0.002$^{[8]}$</td>
<td>0.009$^{[5]}$</td>
<td>0.072$^{[6]}$</td>
<td>0.030$^{[10]}$</td>
</tr>
<tr>
<td>Bus</td>
<td>0$^{[1]}$</td>
<td>0$^{[9]}$</td>
<td>0.001$^{[6]}$</td>
<td>0.009$^{[5]}$</td>
<td>0.037$^{[10]}$</td>
</tr>
<tr>
<td>Environment</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>

NA: Not applicable.
Superscript $^[$ denotes Step $^[$ from Table I.

isolate the role of vehicle mix and vehicle prevalence on fatality rates.

4.2. Computing the Proportionality Constant $K^{\text{threat}}_{\text{victim}}$

In order to compute absolute fatality counts using Equation (4), we need a numerical value for the proportionality constant, $K^{\text{threat}}_{\text{victim}}$, which we estimate based on crash statistics from New Delhi. In 2001, cars and pedestrians had a trip modal share of 18% and 19%, respectively, and the resulting car-pedestrian interactions caused 102 pedestrian fatalities. Thus, using Equation (4) and a pedestrian CFR of 0.08, the two-vehicle proportionality constant, $K^{\text{threat}}_{\text{victim}}$, is approximately 37,000. Similarly, $K^{\text{environment}}_{\text{victim}}$ is approximately 1,000, based on occupant fatalities in single-vehicle car crashes in New Delhi.

4.3. Transport Growth Scenarios

We construct four scenarios of transport growth that represent widely differing motorization pathways. Four transport modes are considered: walking, scooters, cars, and buses, which are assumed to carry 40 people each.

In a review of urban travel in different regions of the world with diverse sociocultural characteristics, public transportation use was found to range from 17% of all motorized trips (Shanghai, China) to 88% (Mumbai, India). The ratio of two-wheeler ownership to car ownership ranged from 1:10 (Belo Horizonte, Brazil) to 4:1 (Chennai, India). Using these results as a guide, we construct transportation growth scenarios such that in each scenario a fixed proportion of all motorized travel is by bus and the remaining motorized travel is assigned between cars and scooters using a fixed ratio. Each scenario starts with an all-pedestrian society and incrementally increases the proportion of trips that involve motorized travel (i.e., travel by scooter, car, and bus) from 0% to 100%. Since bus trips typically involve walking to and from the bus stop, we include half a walking trip for each bus trip. The four scenarios (Fig. 3) are:

- **Base Case**: A total of 40% of all motorized distance traveled in the city is by bus and the ratio of miles traveled by scooter and by car is 1:1. Thus, at the beginning of the scenario all trips are pedestrian. The proportion of trips that involve motorized travel is then increased in increments (40% bus, 30% scooter, 30% car) to 100%.
- **High Bus Use**: A total of 80% of all motorized travel in the city is by bus and the ratio of miles traveled by scooter to those traveled by car is 1:1.
- **High Car Use**: A total of 40% of all motorized travel in the city is by bus and the ratio of miles traveled by scooter to those traveled by car is 1:10.
- **High Scooter Use**: A total of 40% of all motorized travel in the city is by bus and the ratio of miles traveled by scooter to those traveled by car is 4:1.

It should be noted that although these scenarios use extreme road use characteristics of existing transport systems, they are not intended to mimic specific cities. Thus, for instance, a large proportion of motorized travel in Mumbai is by bus but it is not similar to the High Bus Use scenario because the ratio of car to scooter use may be different.

5. RESULTS

Total traffic fatalities resulting from the four transportation growth scenarios are shown in Fig. 4. The fatality trend for the High Car Use scenario has an inverted-U shape similar to the outcome of the crude model in Fig. 2, which is an all car use scenario. At low levels of motorization, the rise in the number of cars
Fig. 3. Four hypothetical transportation growth scenarios: road use modal shares plotted against the proportion of trips that include a motorized component. It should be noted that since bus trips include pedestrian travel, pedestrians are still a part of the transportation system even when 100% of all trips include a motorized component. This “residual” number of pedestrians varies depending on the proportion of bus use in each scenario.

Fig. 4. Change in total traffic fatalities (all road users) computed for four scenarios of growth in motorized travel. A rapid increase in the threat to those using nonmotorized modes, causing total fatalities to rise. At higher motorization levels, the benefit from the reduced number of VRUs dominates the increased threat from the additional vehicles, and the total fatalities fall. Despite the qualitative similarity with the simple model, the fatalities in the High Car Use scenario no longer return to zero even after 100% of all trips include a motorized component. These residual fatalities exist for two reasons: first, unlike the crude model, vehicle occupants have nonzero fatality risks; and second, there are a significant number of pedestrians (bus riders) even when all trips include a motorized component. The magnitude of the residual fatalities, which exist in all scenarios, depends on the final vehicle mix and is highest for the scenarios involving a large number of scooters because of the high CFR of scooter riders.
Traffic fatalities rise and fall only in the High Car Use scenario. In all other cases, fatalities rise monotonically. In the High Bus Use scenario, fatalities continue to rise because even though bus occupants have low CFRs, bus trips include travel as a pedestrian, which is a high-risk travel mode. Similarly, in the High Scooter Use scenario, transportation growth leads to the substitution of a high-risk travel mode (walking) by another high-risk mode (scooters).

Even though transportation growth through car ownership (High Car Use) eventually causes fatalities to have a falling trend, fatalities are higher than those in the High Scooter Use scenario over much of the range of motorization levels and substantially higher than the High Bus Use scenario. The former finding is because although scooter riders do not have the protection of a metal shell (and, thus, have relatively high CFRs), they pose a much smaller threat than cars to other VRUs, who dominate the vehicle mix in all the scenarios considered. The High Bus Use scenario results in lower fatalities than the other scenarios for the entire range of motorization levels because buses result in far fewer additional vehicles (occupancy of 40) leading to a much smaller increase in threat to other road users.

Unlike total fatalities, fatalities per vehicle show a monotonically decreasing trend with increasing proportions of motorized travel (Fig. 5). The decrease is most rapid for scenarios dominated by car or bus use because of the much higher protection offered by these vehicles when compared with scooters; the decrease is slowest for the scenarios that rely heavily on scooter use.

In order to examine the threat posed by each transport mode in the Base Scenario, we use a series of simulations that start by setting all the pairwise CFRs to zero and then progressively return them to their values in Table II. Note that the marginal contribution of each CFR to total fatality is independent of the order in which the CFRs are introduced because crashes between different vehicle pairs are mutually exclusive. In Fig. 6, Curve (1) is generated by setting all CFRs to zero except $r_{\text{carpedestrian}}$, which was set at 0.08. This analysis is similar to the crude model described earlier—only car-pedestrian risks are considered and car occupants are at no risk. As before, the result is a parabola that peaks at 50% motorized travel. Curve (2) is generated by introducing the threat from cars to scooters, $r_{\text{car-scooter}}$. This results in much larger residual fatalities because of the vulnerability of scooter riders to impacts from cars. Curves (3) and (4), which add the threat from cars to occupants of cars ($r_{\text{car-car}}$) and buses ($r_{\text{car-bus}}$), lie only slightly above Curve (2). Thus, the primary threat posed by cars is to pedestrians and scooter riders.

Curve (5), which adds the threat from buses to all road users (i.e., introduces $r_{\text{bus-pedestrian}}$, $r_{\text{bus-scooter}}$, $r_{\text{bus-car}}$, and $r_{\text{bus-bus}}$) produces only a slight increase in fatalities, suggesting that buses contribute little to traffic fatalities in the Base Case. Curves (6) and (7) introduce the additional threat from scooters to pedestrians, $r_{\text{scooter-pedestrian}}$, and to other scooter riders, $r_{\text{scooter-scooter}}$. The additional pedestrian fatalities are large initially, when the amount of motorized travel is small, but fall when the proportion of motorized travel become large. Similarly, the additional scooter fatalities are higher at high levels of motorized travel. The additional threat from scooters to vehicle occupants (Curve (8)) results in a negligible increase in fatalities.

Curves (9) and (10) add the fatalities from single-vehicle crashes. Scooter fatalities make up a large proportion of these fatalities (Curve (9)). As expected, most of the additional fatalities from single-vehicle crashes occur when the proportion of motorized travel is high. Finally, Curve (11) adds the few fatalities that occur among scooter riders due to impacts with pedestrians to yield the Base Case.

### 6. DISCUSSION

While it is common to ascribe the increase in traffic fatalities that occurred prior to the 1970s in the rich countries to growth in vehicle fleet, the subsequent fall
in fatalities is usually attributed to the introduction of safety programs (see, for instance, World Report on Road Traffic Injury Prevention\(^1\)). Our analyses, using both a simple model of cars and pedestrians and a more complete model that includes a broader vehicle mix, demonstrates that the rise and fall in fatalities per capita and the fall in fatalities per vehicle observed in historical data\(^3\) can also occur due to the interplay of the increased safety afforded by using a vehicle and the increased threat that each additional vehicle poses to VRUs. This inverted-U pattern in fatalities is not driven by a similar rise and fall trend in the number of accidents. In fact, in the crude model the number of accidents, \(\sim (N - C) \cdot C + C \cdot C\), grows linearly with increasing cars. Instead, in our model the fall in fatalities occurs because the vehicle mix shifts from predominately VRUs with high CFRs to vehicle occupants who have low CFRs. These results are consistent with the findings of Bishai et al.\(^{18}\) who analyzed fatality, injury, and accident rates in 41 countries and found that even though fatalities decrease in richer countries with increasing income, the number of crashes continues to rise. However, it should be noted that the model ignores nonfatal injuries, which represent a significant fraction of the public health burden of road traffic crashes, and should be included in a more detailed analysis.

Fatalities per capita fall even though we hold the CFR of each victim-threat pair constant in time and thus do not include the effects of most safety interventions. Safety interventions, of course, have a crucial role in the dynamics of traffic fatalities. Depending on when an intervention is introduced, it acts to either decrease the rate of rise or hasten the fall in traffic fatalities.

Our results suggest that the vehicle mix in alternative scenarios of transportation growth influences both the form of the time pattern and the absolute levels of traffic fatalities. In the absence of safety interventions, the inverted-U form of total traffic fatalities occurs only in transportation scenarios dominated by car use. In the presence of vulnerable modes of motorized transport (such as scooters, mopeds, and motorcycles), traffic fatalities continue to increase with motorization. Interestingly, the scenario involving high scooter use results in traffic fatalities that are similar in magnitude to those resulting from the scenario involving high car use. This is the case because even though scooter riders are at much higher fatality risk than car occupants, they pose a much smaller threat to other road users. Thus, the aggregate outcomes of the two scenarios are similar.

Historic data (Fig. 2B) show a monotonically falling trend in fatalities per vehicle. In our analysis a similar trend is observed for all transport growth scenarios because of the steady decline in the population of VRUs. However, it should be noted that Equation (3) suggests that a decline in fatalities per
vehicle could also occur if vehicle occupancy was to fall over time as often happens with income growth. Traffic fatalities are lowest in the scenario dominated by bus use. This result should be interpreted with caution because our experience with a local model of traffic fatalities suggests that buses can pose threats that have not been included in this analysis. Crash statistics from New Delhi indicate that our model probably underestimates the number of bus rider fatalities and bus-related pedestrian fatalities, many of which occur at bus stops.\(^{(13)}\) Aggressive driving by bus operators coupled with poorly designed bus shelters that force passengers to wait on the street can lead to a much higher rate of bus-pedestrian crashes than estimated by our model. Clearly, these effects should be included in local applications of the model, especially when evaluating the impacts of targeted interventions. For example, in the high-capacity bus systems of Curitiba, Brazil, and Bogotá, Colombia, suitable infrastructure and design (e.g., dedicated bus lanes and bus shelters) have reduced the risks to passengers waiting for and boarding buses, resulting in a much safer bus transportation system.\(^{(16)}\)

Other shortcomings and assumptions of this model can be classified into two sets:

- **Assumptions related to crash probability:** In this initial application, we model crash risk as a linear function of vehicle use, which assumes that all vehicles (as well as pedestrians) share the same roadway. While such mixing of motorized and nonmotorized modes is uncommon in industrialized nations, shared road use is common in the urban centers of many developing countries. Appropriate adjustments to exposure can be made to model scenarios where traffic is less homogeneous. We also assume that total miles traveled remains constant and the only change is through shift in transport modes. Experience from cities worldwide suggests that during economic growth, growth in motorized trips outstrips road building, leading to higher vehicle densities (congestion), and, thus, an increase in the number of crashes (see also below).

- **Assumptions related to the CFR:** Since the CFR matrix is largely derived from U.S.-based studies, it may underestimate the true fatality risks expected in the developing world. However, the CFRs in Table II have a range of two orders of magnitude, and small changes in these CFRs do not significantly alter the fatality trends. Furthermore, we hold the CFRs constant in time in order to isolate the effects of vehicle mix and prevalence on fatality outcomes. As with the probability of crash (discussed above), traffic congestion can have a considerable effect on CFRs because it reduces crash speed. At speeds of about 30 km/h, the crash speed has a larger effect on bicyclists and pedestrians than on occupants.\(^{(8,10)}\) In our analysis, a 5% decrease in crash speed causes the traffic fatality trend of the Base Case to be uniformly lowered by approximately 7%; an increase in speed of 5% causes fatalities to increase by approximately 25%

Detailed calibration of the model against real-world data is needed before it can be applied to policy analysis. In the absence of such data, we have applied the methodology to perform a qualitative exploration of traffic fatality outcomes for hypothetical transportation growth scenarios. However, when detailed information about the traffic stream is known for a particular region (country, city, or traffic corridor), suitable crash-risk models can be developed (see, for instance, Reference 17). These locally validated models can be used for long-term regional planning (e.g., identifying optimal vehicle mix, and evaluating the impact of dedicated bus lanes) as well as for the evaluation of short-term targeted interventions (e.g., speed limits and motorcycle helmets) that are implemented over time periods in which the basic characteristics of the transportation system remain constant.

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