Income, Income Inequality and the "Hidden Epidemic" of Traffic Fatalities

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Abstract: Few, if any, epidemics responsible for 20 million severe injuries and/or deaths each year, globally, receive less public attention than do traffic accidents truly making them a "hidden epidemic". Worse yet, the epidemic is growing as evidenced by World Health Organization data which show deaths from traffic accidents increasing by 20 percent between 1990 and 2002. In this paper we examine how a country's stage of development and its distribution of income affect its traffic fatality rate. In our theoretical analysis, we show that traffic fatalities should have a nonlinear relationship with a country's level of per capita income while being a decreasing function of income equality. We test our model's predictions by evaluating data from 79 countries between 1970 and 2000, taking into account other factors that influence traffic fatalities like the motorization rate, health care networks, education, and alcohol consumption and find strong evidence of the theoretical model's predictions. Specifically, the empirical results indicate that traffic fatalities are negatively related to income equality throughout its range and also are negatively related to per capita income, above a threshold of about $11,500.

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1. Introduction

Road traffic accidents are a major and growing global public health problem affecting all sectors of all societies. According to the World Health Organization, worldwide deaths from road traffic accidents have risen from approximately 999,000 in 1990 to 1.2 million in 2002 and are projected to approach 2 million per year by 2020. This represents an average of 3,000 people being killed daily in road traffic accidents, globally. It is important to note, however, that while all regions of the world are affected by road traffic accidents, developing countries bear a much greater burden than do their relatively more developed counterparts. As evidence, consider that while accounting for only 40 percent of the world's motor vehicles, developing countries suffer 85 percent of total road traffic casualties annually (Jacobs et al 2000).[1]

Contrary to relatively developed countries where most traffic deaths involve auto and truck drivers, in developing countries those who enter roadways as pedestrians, bicyclists, bus/minibus passengers, and motorcyclists account for 90 percent of all traffic-related deaths and injuries (Nantulya and Reich 2003). In these poorer countries, pedestrians alone account for up to two-thirds of casualties from accidents occurring in urban areas, while in rural areas the majority of victims are passengers on buses or minibuses operating between small towns and cities. Road use in these countries is particularly risky because modern public transportation infrastructures and systems are often lacking forcing the poor, by being unable to afford private cars, into informal communal transportation networks which often involve overcrowded and relatively unregulated privately-owned buses, minibuses, taxis and, at times, pick-up trucks.[2] To the poor, this transport mode is affordable and readily available. However, while cheap and convenient, such travel often relies on untrained and poorly skilled drivers, lacking job security or insurance, and who work long hours resulting in

[1] In 2000, road traffic accidents resulted in the deaths of more than 1 million people in low- to middle-income countries compared with 125,000 in high-income countries (Feigenblatt, 2003).

[2] This transport mode includes "the *matatas* in Kenya, ... the *jeepneys* of Manila, the *Colt* of Jakarta, the *dolmus-minibus* of Istanbul, the *dala dala* of Tanzania, the *tro-tro* of Ghana, the *tap-tap* of Haiti, the *molue* (locally dubbed 'moving morgues'), and *danfo* ('flying coffins') of Nigeria" (Nantulya and Reich, 2003, p. 17).

excessive fatigue and sleep deprivation, leading to high rates of fatal road accidents.[3]

Taken together, these examples show a rather clear connection between a country's level of development and its rate of traffic fatalities. Exploring this, Kopits and Cropper (2005) test the relationship between per capita income and a country's traffic fatality rate (fatalities/population) and report an inverted U-shaped relationship suggesting that traffic fatalities may be, at least for relatively poor countries, a negative externality related to the development process. The intuition of this outcome is fairly straightforward and turns on the observation that as per capita income rises, two opposing forces are put into action that bear on a country's traffic fatality rate; an increasing rate of motorization (vehicles/population) and a decreasing rate of fatalities per vehicle (fatalities/vehicle), given the occurrence of an accident. These two forces are essential to understanding a country's traffic fatality rate in that the fatality rate is, by definition, equal to their product.

The observation that increases in per capita income can be expected to lead to increases in a country's motorization rate flows from the fact that cars and other private motor vehicles are luxury items, as has been shown in a number of empirical analyses (see fn. 11). The rate of increase will be most pronounced in very poor countries which start with low base levels of motorization, but remains positive throughout any reasonable scale of per capita income. As the rate of motorization increases, so do roadway congestion and the resulting likelihood of potentially fatal accidents, thus the increase in motorization tends to put upward pressure on a country's traffic fatality rate.

Serving to initially partly and eventually fully offset the effects of increasing motorization are a number of private and public actions likely to be taken as per capita income increases which serve to increase roadway safety, thus reducing fatalities per vehicle, and consequently putting downward pressure on a country's traffic fatality rate. Numerous examples of these actions can be identified. On the private side, the

[3] Examples of unsafe driving habits of these drivers (such as ignoring red lights and dangerous overtaking of other vehicles) abound. Nantulya and Reich (2003, p. 17) report that "the driver of one *danfo*, meaning 'flying coffin', in Nigeria swung his vehicle from his lane into the opposite lane, to beat a traffic snarl-up, and sped on until he encountered an oncoming truck that would not yield. The *danfo* was flung in the Lagos Lagoon and all the occupants drowned. ... [T]wo buses collided on a bridge near the coastal town of Malindi in Kenya, and both plunged into the river, leaving over a hundred passengers dead. The two buses were reported to have been racing each other for 20 kilometers in order to get to Malindi first to pick up other passengers."

increased motorization brought on by rising levels of income eventually serves to add to the driving experience of car owners leading to safer motorists. Similarly, increased experience with sharing roads with motorized vehicles on the part of those walking or cycling on roadways reduces the likelihood of their being involved in an accident with a motor vehicle. In either case, the growing experience of all road users should serve to pull down both fatalities per vehicle and the overall fatality rate. Similarly, with rising levels of per capita income, individuals can afford higher quality, safer vehicles, as well as more readily afford to keep them in safe working condition.

Complementing these private actions, and perhaps of greater importance, are various public actions that tend to come into play as per capita income rises that put downward pressure on fatalities per vehicle and the overall traffic fatality rate. These might include more fully-developed roadway infrastructures, traffic calming devices, improved traffic flow measures, pedestrian walkways that separate walkers from motor vehicles, safety inspections of vehicles, stricter driver testing and licensing, seat belt and other safety restraint requirements, regulations on alcohol consumption while driving, and implementation and effective enforcement of traffic control rules.[4] Public actions that lead to improved systems for preliminary treatment and transportation of those injured in accidents and improved public health care networks can also be expected to prove effective in reducing traffic fatalities. Of course, these and other similar public actions require significant public sector investment. And the ability to make such investments is clearly limited by the per capita income level of a country's population, or put differently such investments should be an increasing function of per capita income.

Consequently, as per capita income rises, the motorization rate can be expected to rise, but at a declining rate. At the same time, the rising level of income tends to lead to private and public actions that cause fatalities per vehicle to fall and, most importantly, these actions can be expected to come into being at

[4] Empirical evidence points to the efficacy of these and other traffic-safety interventions. Chaloupka, Saffer and Grossman (1993), Mast, Benson, and Rasmussen (1999), Ruhm (1996), Rasmussen and Benson (1999), and Dee (1999) all show the positive effects of alcohol control policies on traffic safety. Others have shown the effectiveness of mandatory seatbelt laws such as Bhatacharyya and Layton (1979), Houston, Richardsson, and Neely (1995), and Cohen and Einav (2003).

an increasing rate. Given these two forces, a typical, very poor country can be expected to suffer through an increasing rate of traffic fatalities as it develops, at least until the per capita income level is reached at which the positive effect of the falling rate of fatalities per vehicle fully offsets the negative effect of the growing rate of motorization. Beyond this threshold level of per capita income, further increases in income will be accompanied by a falling rate of traffic fatalities as the falling rate of fatalities per vehicle more than offsets the rising motorization rate.

While we fully accept the findings and underlying explanations of Kopits and Cropper (2005) linking per capita income and the traffic fatality rate, it is our contention that while the average level of income within a country is clearly an important determinant of its traffic fatality rate, also important is the distribution of income within a country, a relationship that has yet to receive rigorous attention in the literature. To be more precise, it is our belief that, at any given level of per capita income, a country's traffic fatality rate can be expected to be greater the more unequal is its distribution of income. While there may be numerous factors leading to this outcome, we stress two of the most important. The first and perhaps most obvious concerns the various traffic safety interventions noted above which require significant public funding. Before investments into traffic safety interventions or any other public good can be made, there must be agreement between parties as to how the tax burden necessary to fund the projects will be distributed. When national income is relatively equally distributed, the likelihood of reaching such an agreement is much greater than when a relatively few hold a disproportionately large share of the nation's income. In the latter case, rather that agreeing to contribute what they might see as an unfair share of the cost of the public actions, it seems reasonable to assume that at least some of those in the relatively well-off segment of society will oppose the public actions and attempt to self-insure against traffic fatalities through actions such as limiting their road travel, owning the safest cars available or hiring professional drivers. Thus, while the public actions might eventually come into being, income inequality is likely to slow the rate of investment in these actions. To the extent that this occurs, for any given level of per capita income, a country can be expected to have a higher rate of traffic fatalities when it has a more unequal distribution of income than when that distribution is more equal. [5]

Also explaining our perspective on the role of inequality is our contention that inequality causes a country's income-diverse population segments to enter roadways in very different fashions and this difference in mode of entry contributes to a positive relation between inequality and fatality rates. For example, consider a very poor country with a near perfectly equal distribution of income. Since all members of the society have roughly the same income, they will likely be found entering roadways in much the same mode—perhaps all (or nearly all) being pedestrians, or, if the level of income is greater as operators of modest vehicles. If nearly all enter roadways as pedestrians, while some deaths will occur due to accidents involving these road users and commercial vehicles, buses and the like, the number is likely to be rather low. Similarly, if nearly all enter roadways, due to having roughly the same income, as operators of similar, modest motor vehicles, the traffic fatality rate, while likely being a bit higher than in the prior case, will also prove comparatively modest. That is, while the fact that most of the population now drives serves to minimize the possibility of the type of accident that proves most often fatal—those involving pedestrians—it also leads to more congestion and thus more vehicle-to-vehicle accidents, some of which will prove fatal. To be sure, in neither case will the fatality rate of such a country be zero, but it should be lower than if the country maintained the same per capita income level, only with a much more unequal distribution. This is because an unequal distribution of income will leave the largest segment of the population entering roadways as pedestrians while the few with relatively high incomes are able to afford to operate their own cars. Consequently, the country's poor will suffer substantially greater fatality risks as they face, on foot, the increased congestion from their now more motorized wealthier counterparts as well as the risk they face from commercial vehicles and buses. In this case, those entering roadways on foot are at much greater risk than

[5] See Anbarci, Escaleras, and Register (2005) for a detailed theoretical and empirical analysis of a setup in the context of earthquake disaster hazard where in some environments different segments of society prove incapable of arriving at an equitable distribution of the tax burden of the necessary collective action, causing the relatively wealthy to simply self-insure against the disaster while leaving the relatively poor to its mercy.

they would be if a more equal distribution of national income had caused all or nearly all to enter as either pedestrians or drivers. It is the similarity or dissimilarity of the mode of entry by differing groups within society that is the key to determining the actual level of traffic fatalities. When income is low but rather equally distributed, most of the population will enter roadways in a similar fashion, thus minimizing the traffic fatality rate. On the contrary, when the same level of income exists but that income is unequally distributed, this inequality causes segments of the population to enter roadways in significantly different modes, leading to greater, general traffic fatality rates.

While the dynamics are a bit different, the impact of inequality on traffic fatalities is much the same in a high-income country. Once again, consider a country with a perfectly or nearly perfectly equal distribution of income, but now assume that this is accompanied by a very high level of per capita income—one so high that all who wish to, can afford to own and operate a motor vehicle. Given that all members of society have roughly equal incomes, variations in the types of vehicles operated will be minimal, determined entirely by differences in tastes rather than differences in both tastes and income as would be the case if incomes varied. In this situation, while crashes will occur, some of which prove deadly, the fact that the vehicles involved will tend to be of similar type, and most importantly from a safety perspective, of similar size will serve to minimize the traffic fatality rate. This can best be seen by relaxing the assumption of a near perfectly equal distribution of the country's very high national income. If per capita income remains the same, but becomes much more unequally distributed, the traffic fatality rate can be expected to increase as, as was true in the poor country, income inequality causes the differing segments of society to enter the roadways in different fashions. The primary cause of this is the fact that as income inequality grows variation in vehicle choices also grow. The relatively wealthy, having satisfied their basic needs for transportation, begin to demand other attributes in their cars such as enhanced safety, greater performance, greater utility, more technological sophistication, and the like. These attributes, on average, tend to drive up the price of cars and also result in the wealthy driving relatively large and heavy vehicles. This assumed relationship between price and size becomes immediately apparent upon consideration of any of the numerous, readily available new vehicle pricing and specifications guides.[6]

At the same time, their relatively less wealthy counterparts, lacking the income to make such choices, are confined to the part of the market in which basic transportation is the primary attribute, thus, they tend to be found driving either reasonably new but smaller, more basic vehicles or perhaps older, larger vehicles which likely lack contemporary safety features and have greater risk of mechanical-failure related accidents. Consequently, the variance in income leads to variance in size, among other safety-related attributes, of the vehicles driven by the wealthy and less wealthy segments of the rich society. The importance of this outcome is that not only do larger vehicles have lower fatality rates, on average, than do smaller vehicles, but variance in car size when accidents occur is a strong determinant of the likelihood of a given accident proving fatal. The former part of this statement—that larger vehicles have lower fatality rates—is easily verified by considering the data and analysis made available by various national highway safety administrations and by insurance industry traffic safety institutes.[7] For example, the U.S. National Highway Traffic Safety Administration notes that in 2004 total occupant fatalities per 100,000 registered vehicles drops from about 18 for compact cars to about 12 for full-sized cars, a relationship that holds for pickup trucks as well as sport utility vehicles. The relatively more important part of the statement for our purposes is that fatalities are more likely when vehicles of disparate size crash than when similarly sized vehicles do so. This outcome has been consistently shown in analyses of actual crashes occurring in the U.S. conducted by the National Highway Traffic Safety Administration, the Insurance Institute for Highway Safety, and by private researchers.[8]

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[6] Two relatively complete, at least for the U.S., online guides are produced by J.D. Power and the Kelly Blue Book (JD Power available at www.jdpower.com and Kelly Blue Book at www.kbb.com).

[7] Examples of national highway safety administration's data and analysis on fatality rates by vehicle size can be found for the U.S. in a number of publications of the National Highway Traffic Safety Administration including Kahane (1997a,b) and Klein, Hertz, and Borener (1991) while similar data for Great Britain is produced by the Department of Transport and can be found at www.dft.gov.uk/stellent/groups/dft_tansstats/documents/page/dft_transstats_508326.hcsp. Insurance industry-based data on the issue can be found for the U.S. on the Insurance Institute for Highway Safety's website at www.iihs.org/research/default.html and for Canada at the website of the Insurance Bureau of Canada at www.ibc.ca/vehinfo_pub_howcarsmeasureup.asp.

[8] See, for examples, National Highway Traffic Safety Administration (1994 and 1998), the Insurance Institute for Highway

Relative to a situation in which all or most of a population operate similarly sized vehicles, inequality can in this way be expected to lead to greater variation in the size of vehicles operated and, consequently to an increase in the traffic fatality rate as these vehicles of disparate size inevitably crash. The key is that inequality, just as in the case of a poor country, leads the relatively rich and poor to enter roadways in very different fashions and it is this dissimilarity in mode of entry that is key in the determination of the traffic fatality rate. Of course, this is not to suggest that the marginal effect of inequality should be the same in rich and poor countries. While being a driver of a small car encountering a large car does increase one's risk above what it would be were all driving similarly sized cars this increase in risk is not likely to be as dramatic as in the case where inequality leads to pedestrians encountering motorized vehicles as is more typical in a poor country. Regardless, by causing the differing segments of society to enter roadways in dissimilar fashions, the effect of inequality should be to increase the traffic fatality rate throughout the income spectrum.

Finally, providing additional support for the idea that income inequality and traffic fatalities are linked, Atkins (1998) reports, based on four developing countries, strong evidence that poorer sectors of a given community are much more likely to be involved in road crashes than are higher income sectors. Similar outcomes have been reported in both the U.K. (Roberts and Power 1996; and Christie 1995) and Sweden (Lafalmme and Engston 2002). In addition, in 2000, the U.K. Government's Road Safety Strategic Plan highlighted the fact that the poorest children were five times more likely to die as pedestrians than the wealthiest children, a result that echoes findings for Montreal by Dougherty, Pless, and Wilkins (1990) who report that children living in that city's poorest neighborhoods were four times more likely to be injured in auto-related accidents than their counterparts in the wealthiest parts of the city.

Consequently, we argue that as a country moves through the various stages of development it can be expected that, beyond some threshold level of per capita income, increases in per capita income will tend to push down the traffic fatality rate as the rate of decline in fatalities per vehicle begins to fully offset the rising

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Safety (1998 and 1999), and Evans and Frick (1993).

motorization rate. Regardless, for any given level of per capita income, the rate of traffic fatalities can be expected to be greater the more unequally distributed is a country's national income both because relative inequality makes it more difficult for a society to agree on a distribution of the tax burden necessary to fund traffic safety interventions and because inequality of income causes the different segments of a society to enter the roadways in different fashions. As such, the goal of the present analysis is to bring the three key variables—per capita income, income inequality, and the rate of traffic fatalities—together both theoretically and empirically. To do so, we first develop a theoretical model that relates these three variables while taking into account the notions of vulnerable road users, motorization rates, and accident probabilities, along with the likelihood that accidents result in deaths. As discussed above, our model shows that road traffic fatalities should exhibit a nonlinear linear relation with a country's per capita income while being a decreasing function of income equality. While the variables and data used in the study are defined and discussed more thoroughly below, to provide some initial insight into the relations we anticipate, we present scatter plots of the relationship between per capita GDP and the traffic fatality rate for the 1,830 country-year observations in our sample of 79 countries between 1970 and 2000 in figure 1 while the relationship for income inequality, as measured by the common gini code, and the traffic fatality rate is offered in figure 2. To provide a bit more statistical structure to these simple plots, table 1 presents univariate difference in means tests of the traffic fatality rates for those observations with relatively high versus low per capita income levels in panel 1(a) and relatively high versus low levels of inequality in panel 1(b).

While obviously embodying a degree of noise to be expected when looking at raw data, figure 1 does offer a fairly well-behaved inverted U-shaped relation between per capita income and the traffic fatality rate, as prior research and the foregoing discussion suggests. To provide a simple test of this apparent relation, we divide the sample at the mean of $8,489 and find that while the high-income countries do have lower rates of traffic fatalities, the difference is not significant. Likely this simply results from the turning point in the inverted U relation being at an income level rather greater than the $8,489 mean level of per capita GDP, as will be shown in the empirical analysis.

Figure 2's depiction of the inequality/fatality rate relationship has the expected positive slope only for those observations with relatively high levels of inequality and only modestly then. More hopeful, however, is the univariate test of the relationship between these two variables using the 38.2 mean value of gini to divide the sample, as presented in panel 1(b). Here we do find evidence that income inequality is positively associated with traffic fatality rates. That is, the rate of traffic fatalities is significantly greater in relatively income-unequal countries than it is in relatively income-equal countries.

While the univariate test offers some support for the existence of a relation between inequality and traffic fatalities, care must be taken in interpreting the multivariate outcomes we present as it relates to this key relation. There is an existing literature on the linkage between income inequality and various health care outcomes when aggregate level data such as we use here is employed, part of which calls into question the conclusion drawn by some that inequality and poor health are causally linked. Specifically, a debate has been taking place in this literature between those who argue that income inequality is a strong determinant of poor health (e.g., Rodgers 1979; Waldmann 1992; Wilkinson 1996; Kawachi, Kennedy, and Wilkinson 1999) and those who feel that no such strong relation exists (e.g., Mellor and Milyo 2001, 2002; Gravelle 1998).[9] There are three common criticisms of the inequality/poor health conclusion. First, if, as is commonly accepted, individual health is a nonlinear function (concave) of individual income, then a relationship can be expected between health outcomes and income inequality when aggregated data are used since income inequality will be serving to proxy the number of people in the population who have low income. This potentially misleading estimated relation between income inequality and health outcomes is referred to as an ecological fallacy or a statistical artifact. A second common criticism is that the proponents of the inequality/poor health link fail to offer a theoretical defense of their proposition and often even fail to offer a persuasive intuition for it. Finally, these studies are criticized for omitted variables bias, typically associated with poor or no controls

[9] See Deaton (2003) for a thorough review of the various aspects of this debate.

for income, other socio-demographic factors, and time and locality.

Since we do wish to relate inequality and traffic fatality rates, it is incumbent upon us to address these criticisms. Perhaps least satisfying is our reply to the first criticism which is that, given our goal, we have no option but to use aggregate data. That is, while we would prefer the option of using data of a more micro-nature, such data does not exist. We are able to offer more positive replies to the second and third criticisms, however. Unlike much of the research pointing to an inequality/poor health relation, we develop and test a theoretical model, based on the intuitive arguments for an inequality/traffic fatality relationship discussed in detail above. Further, in the empirical modeling that follows, we take steps to address, to the extent possible, the omitted variables bias criticism in that we control for, among other things, income, in several different ways, socio-demographic factors, time, and location. Finally, it is important to specifically note the work of Mellor and Milyo (2001) which uses U.S. state level data in an attempt to assess the existence of an ecological fallacy in prior work that pointed to a link between inequality and poor health outcomes. Mellor and Milyo consider the relation between inequality and nine measures of health outcomes and find that in most instances, once a number of previously omitted demographic factors are included as well as regional and time effects, the inequality/poor health outcome disappears. Interestingly, however, one of the three cases in which this does not occur, or at least not fully, is that of general accident rates. To the extent that general accident rates and traffic accident rates behave similarly, this finding provides support for the estimated relation between inequality and traffic fatalities that we identify. To be sure, however, we accept this existing literature as indicating that some degree of caution should be applied when drawing our conclusions.

In preview of the multivariate results, we find what we take to be strong and consistent support of the expected relations between the primary variables of interest, the traffic fatality rate, per capita income, and income inequality. Specifically, given the standard caveats involved with empirical analysis and, especially, the specific caveat just discussed, our findings indicate that road traffic fatalities are a negative function of income equality and, above a level of about $11,500 per capita, the level of income within a country.

The remainder of the paper is organized as follows. Section 2 lays out the basics of the theoretical model of the joint relationship of per capita income and income inequality with road traffic fatalities. Section 3 discusses the data to be analyzed. Section 4 presents the multivariate analysis and results, while a summary conclusion is presented in the paper's final section.

2. Theoretical model

Our analysis starts with the premise that there are two types of households in society: L-types (low-income households), and H-types (high-income households). We assume that the measure of all households is one. Within society, the fraction of low-income type households is $L \in (0,1)$, and thus the fraction of high-income type households is $H = 1-L$. An L-type household's income is denoted by $y_L \in [\varepsilon,1)$ where ε is an arbitrarily small positive real number, and that of an H-type by $y_H \in [\varepsilon,1)$ such that $y_H = k\, y_L$, where $k \geq 1$. That is, k denotes the extent of income inequality in society (observe that $k = 1$ implies that society has perfect income equality). Per capita household income is $\underline{y} = L\, y_L + (1-L)\, y_H$.

The probability that a household i owns a four-wheeled motor vehicle[10] is given by $p_i = y_i^{\alpha}$ where $\alpha > 1$. Observe that, given k, a high-income household's probability of owning a car is k^{α} times the probability of a low-income household doing so. Thus, motor vehicles, as empirical estimates of motor vehicle income elasticities suggest, are luxury items.[11] *Motor-vehicle users* are those households owning four-wheeled motor vehicles. The average probability that a household owns a motor vehicle is $p_M = L\, p_L + (1-L)\, p_H$, which we denote as the *motorization rate*. On the other hand, *vulnerable users* include those road users who are pedestrians, motorcyclists, bicyclists, or who take advantage of any informal communal transportation networks that exist. The probability of being a vulnerable user is $1-p_M$.

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[10] We do not include motorcycles in the motor vehicles category as, due to their high rates of serious injuries, their riders are best considered vulnerable road users.

[11] McCarthy (1996), using data from the U.S. found that the income elasticity of demand for cars is 1.70. Many studies cited therein also report income elasticity values for cars which are well above unity. Economist (1998), based on various international studies, concludes that income elasticity of demand for cars is about two.

There are two types of fatal accidents; those taking place when two motor-vehicles collide, and those that take place when a motor-vehicle and a vulnerable user interact. The probability that a motor-vehicle user and a vulnerable user will encounter each other is the product $p_M\,(1-p_M)$; note that the latter reaches its peak when $p_M = (1-p_M)$. There are three possible scenarios for vehicle-to-vehicle accidents: (1) both motor vehicles belong to H-types, (2) both motor vehicles belong to L-types, and (3) one of the motor vehicles belongs to an H-type while the other one is owned by an L-type. The probabilities of these accidents taking place will be (1) $H\,p_H\,H\,p_H$, (2) $L\,p_L\,L\,p_L$, and (3) $H\,p_H\,L\,p_L$, respectively.

When two parties crash into one another on a roadway, the probability of a fatal outcome depends primarily on two factors: (i) the relative sizes of the cars as well as the overall number of cars involved, ceteris paribus, and (ii) the existing traffic infrastructure (especially road and vehicle conditions) and the existence and enforcement of specific safety interventions. Most safety interventions have strong publicly-consumed natures and, as such, investment in them depends on the level of the per capita income in society, if we assume a given distribution of income. Thus, given an encounter between two parties, the probability of a fatal outcome will be inversely related to per capita income. Let $p_f = (\gamma+\varepsilon)-\underline{y}$ denote the probability that an encounter between two parties will turn out to be deadly where $\gamma > 1-\varepsilon$ is arbitrarily close to 1.[12] This probability, $p_f = 1-\underline{y}$, will decrease in the level and implementation of traffic safety interventions, since the latter increase in $\underline{y}$. Observe that as $\underline{y}$ tends to 1 (which is $\underline{y}$'s upper limit), p_f tends to 0 (but since y_H is less than 1, p_f will always be positive). As $\underline{y}$ tends to ε (which is $\underline{y}$'s lower limit), p_f tends to $\gamma = 1-\varepsilon$ (which is very close to 1).

The link between the relative sizes of vehicles involved in an accident and the likelihood of fatalities is critical to the model. As was discussed in the introduction, the severity of an accident and thus the likelihood of a fatal outcome are strongly correlated with the relative sizes of vehicles involved. This, no doubt, will be magnified by inequality in society given the strong positive correlation between vehicle size

[12] As data indicate, fatalities per vehicle (which, conceptually, is very close to our p_f) is a decreasing function of per capita income—except in the poorest of countries.

and price, as noted above. But there are two more channels through which inequality can be expected to affect traffic fatalities. First, particularly in poorer countries, as inequality increases so does the disparity between motor vehicle users and vulnerable road users in the fashion in which each group enters roadways. Second, inequality will increase the number of cars in operation since $p_M = L\ p_L + H\ p_H$ is a convex function (to see this recall that $p_i = y_i^{\alpha}$ where $\alpha > 1$); and as the number of cars increases, so will their probability of a crash occurring between them, ceteris paribus. As an example, suppose all members of society have income of 1/2 and $\alpha = 2$. Given this, the probability of a household having a car is 1/4; since the total measure of the population is one, $p_M = 1/4$. Now consider a different case in which each H-type household has an income of 3/4 and each L-type household has an income of 1/4. Further suppose that each group has an equal number of households (i.e., L = H = 1/2). In this case, the probability of an H-type household owning a car is 9/16 and the probability of an L-type owning a car 1/16. Hence, p_M will be 1/2 (9/16) + 1/2 (1/16) = 5/16. Note that in the more unequal latter case, there are more cars in operation than in the initial egalitarian case.

Regarding the impact of the relative sizes of the cars on the lethality of the accidents, a convenient hierarchy is as follows: the deadliest accidents are those involving motor vehicle users and vulnerable users. We will assume that such an encounter will turn deadly with probability $p_f = 1-\underline{y}$. Somewhat less lethal would be accidents between two motor vehicles of disparate size (one belonging to an H-type with the other belonging to an L-type). These accidents will turn deadly with probability $(1-\underline{y})[t+(p_H-p_L)]/2$ (i.e., with $p_f\ [t+(p_H-p_L)]/2$) where $1 > t > 0$ (as will noted later, this assumption is not necessary for our result). Finally, least lethal are accidents between two motor vehicles of similar size, which prove deadly with probability $(1-\underline{y})t/2$.

Hence, the traffic fatality rate, TFR, is

$$TFR = [t\ H\ p_H\ H\ p_H + t\ L\ p_L\ L\ p_L + (t+(p_H-p_L))\ H\ p_H\ L\ p_L + p_M\ (1-p_M)]\ p_f/2 \text{ where } 1 > t > 0. \quad (1)$$

Theorem 1: *(i) The traffic fatality rate, TFR, always increases in inequality in society. In fact,* *each of the following components of TFR always increases in inequality: (1) [t H p_H H p_H + t L p_L L p_L] p_f/2, (2) [(t+(p_H-p_L)) H p_H L p_L] p_f/2, and p_M (1-p_M)] p_f/2.*

(ii) TFR first increases and then decreases in society's per capita income.

Proof: (i) Note that [t H p_H H p_H + t L p_L L p_L] p_f/2 reduces to [t H^2 $(y_H)^{2\alpha}$ + t L^2 $(y_L)^{2\alpha}$] (1-$\underline{y}$)t/2. Consider a mean-preserving spread of y_L and y_H around $\underline{y}$ (i.e., consider an increase in k which leaves $\underline{y}$ intact). Then, by using Jensen's Inequality, [t H^2 $(y_H)^{2\alpha}$ + t L^2 $(y_L)^{2\alpha}$] will increase (while (1-$\underline{y}$)t/2 remains the same) in such a mean-preserving spread (i.e., in an increase in k). Next consider the second component of TFR, namely [(t+(p_H-p_L)) H p_H L p_L] p_f/2. Note that [(t+(p_H-p_L)) H p_H L p_L] p_f/2 reduces to [(t+($(y_L)^\alpha$-$(y_H)^\alpha$) H $(y_H)^\alpha$ L $(y_L)^\alpha$](1-$\underline{y}$)t/2. Clearly, both $(y_L)^\alpha$-$(y_H)^\alpha$ and $(y_H)^\alpha$ $(y_L)^\alpha$ increase in a mean-preserving spread (i.e., in k). Thus, as was mentioned before and will be emphasized again below, even in the absence of the part $(y_L)^\alpha$-$(y_H)^\alpha$ (i.e., even if we assumed that such an accident would turn deadly with probability (1-$\underline{y}$)t/2), our result would hold. Finally, consider p_M (1-p_M)] p_f/2. p_M (1-p_M) reduces to (L $(y_L)^\alpha$ + H $(y_H)^\alpha$)[1 - (L $(y_L)^\alpha$ + H $(y_H)^\alpha$)]. Again, by using Jensen's Inequality, this component of TFR will increase in such a mean-preserving spread (i.e., in k).

(ii) Now consider an increase in the per capita income $\underline{y}$. We will first show that [t H p_H H p_H + t L p_L L p_L + (t+(p_H-p_L)) H p_H L p_L + p_M (1-p_M)]/2 < $(y_H)^\alpha$ holds. To see this first note that [t H p_H H p_H + t L p_L L p_L + (t+(p_H-p_L)) H p_H L p_L + p_M (1-p_M)]/2 reduces to [t H^2 $(y_H)^{2\alpha}$ + t L^2 $(y_L)^{2\alpha}$ + (t+($(y_L)^\alpha$-$(y_H)^\alpha$) H $(y_H)^\alpha$ L $(y_L)^\alpha$ + ((L $(y_L)^\alpha$ + H $(y_H)^\alpha$)(1 - (L $(y_L)^\alpha$ + H $(y_H)^\alpha$))]/2. Next note that (i) (t H^2 $(y_H)^{2\alpha}$ + t L^2 $(y_L)^{2\alpha}$)/2 is less than (t (H^2+L^2)$(y_H)^{2\alpha}$)/2, (ii) [(t+($(y_L)^\alpha$-$(y_H)^\alpha$) H $(y_H)^\alpha$ L $(y_L)^\alpha$]/2 is less than (2t HL $(y_H)^{2\alpha}$)/2 and (iii) [(L $(y_L)^\alpha$ + H $(y_H)^\alpha$)(1 - (L $(y_L)^\alpha$ + H $(y_H)^\alpha$)]/2 is less than [(H+L) $(y_H)^\alpha$ (1- (H+L) $(y_H)^\alpha$)]/2. The latter, [(H+L) $(y_H)^\alpha$ (1-(H+L) $(y_H)^\alpha$)]/2, becomes [(H+L) $(y_H)^\alpha$ – $(H+L)^2$$(y_H)^{2\alpha}$]/2 Thus, [t H^2 $(y_H)^{2\alpha}$ + t L^2 $(y_L)^{2\alpha}$ + (t+($(y_L)^\alpha$-$(y_H)^\alpha$) H $(y_H)^\alpha$ L $(y_L)^\alpha$ + ((L $(y_L)^\alpha$ + H $(y_H)^\alpha$)(1 - (L $(y_L)^\alpha$ + H $(y_H)^\alpha$))]/2 is less than (t (H^2+L^2)$(y_H)^{2\alpha}$)/2 + (2t HL $(y_H)^{2\alpha}$)/2 + [(H+L) $(y_H)^\alpha$ – $(H+L)^2$$(y_H)^{2\alpha}$]/2. In the latter term, $(H+L)^2$$(y_H)^{2\alpha}$ is equal to [(H^2+L^2)$(y_H)^{2\alpha}$ + 2 HL $(y_H)^{2\alpha}$].

Therefore, $(H+L)^2(y_H)^{2\alpha}$ is greater than $t[(H^2+L^2)(y_H)^{2\alpha} + 2\,HL\,(y_H)^{2\alpha}]$. Hence, $(t\,(H^2+L^2)(y_H)^{2\alpha})/2 + (2t\,HL\,(y_H)^{2\alpha})/2 + [(H+L)\,(y_H)^{\alpha} - (H+L)^2(y_H)^{2\alpha}]/2$ is less than $(y_H)^{\alpha}$. Finally, it is trivial to observe that $y_H^{\alpha}(1-y_H)$ has a maximum at $y_H = \alpha/(1+\alpha) < 1$. But since TFR < y_H, TFR has a maximum at some $\underline{y} < y_H = \alpha/(1+\alpha) < 1$. That is, TFR first increases and then decreases in $\underline{y}$ in the interval $[\varepsilon,1)$. This completes the proof.

First, note that the assumption of motor vehicles being luxury items allows us to use Jensen's Inequality which is crucial in the above proof. Second, note that if we were to assume that accidents between vehicles driven by H-types and L-types (that is, accidents between cars of different size) had the same probability of a fatal outcome as would be the case for accidents involving cars of the same size, $(1-\underline{y})t/2$, our result would hold. That is, the assumption made above, that lethality increases with the variance of the vehicles involved in an accident, while supported in the literature, is not essential to the model.

To link Theorem 1 to the various development stages of different countries, consider the discussion of the following cases:

(i) *A typical developed country*: Such a country, if typical, will have a very high $\underline{y}$ and a relatively low k. In this case, p_M will be high as well. Consequently, $p_M\,(1-p_M)$ will be rather low, and since p_f is also very low, overall $p_M(1-p_M)p_f$ will be very low as well; thus, as suggested above, in developed countries, one can expect to find a relatively small fraction of traffic deaths involving vulnerable users. From the opposite perspective, the total accident probability among motor vehicles, $H\,p_H\,H\,p_H + L\,p_L\,L\,p_L + H\,p_H\,L\,p_L$ will be rather high, but since p_f is very low, overall, deaths from motor vehicle collusions will also be rather low. Consequently, while there will be, overall, relatively few traffic deaths in developed countries, a large fraction of these deaths can be expected to involve drivers or passengers of motor vehicles.

(ii) *A typical middle-income country*: Such a country, if typical, will have a lower level of $\underline{y}$ and a higher level of k than a typical developed country. In this case, since p_M is convex and monotone increasing in $\underline{y}$, the fraction of motor vehicle users, p_M, will be significantly lower and the fraction of vulnerable users will be significantly higher than would be found in a relatively more developed country. Consequently, p_M (1-p_M) will be close to its peak and, equally importantly, p_f will also be comparatively high. Thus, the product, p_M(1-p_M)p_f, will be very large leading to a very high fraction of traffic deaths in developing countries involving vulnerable users. At the same time, the total accident probability among motor vehicles, H p_H H p_H + L p_L L p_L + H p_H L p_L, and p_f will each be rather large. Given this, deaths from motor vehicle collusions will also tend to be large. Nevertheless a smaller fraction of traffic deaths in developing countries can be expected to involve drivers or passengers of motor vehicles. Overall, however, the traffic fatality rate of developing countries will be very high compared to that of developed countries.

(iii) *A typical low-income country*: Such a country, if typical, will have rather low levels of both $\underline{y}$ and k. In this case, p_M will be almost non-existent and even though the fraction of vulnerable users will be extremely high they will not be exposed to a very high fatality risk since p_M (1-p_M) will be very close to zero as will be deaths from motor vehicle collusions. Hence, any traffic fatalities will come from the effect of p_f which will be very high in such countries.

3. Data

To test the main assertions of the theoretical model, our empirical analysis examines the impact of per capita income and the distribution of income within a society on traffic fatalities. The primary implication of our theoretical model is that high levels of per capita income (that is, per capita income above a threshold level) coupled with a more equal distribution of income within a society should be related to lower traffic fatality rates. In our attempt to determine these relations we use data that is both cross-country and cross-time rather than focus on micro-level data that would be limited to a single country or part of a country. The pooled sample is made up of country-year observations for the 31 year period 1970-2000. Were the panel to be balanced, the sample size would be 2,449. Due to the fact that some countries did not provide traffic fatality data for specific years, the primary sample is an unbalanced panel of 1,830 observations from 79 countries.

These include 23 African countries, 12 from the Americas, 26 from Europe, and the remaining 18 from Asia. Table 2 provides a list of the countries making up the primary sample along with the number of years, if any, that each was omitted due to missing traffic fatality data. It is important to note that there does not seem to be a continent-specific pattern to the omissions. For example, in the Americas, while Colombia was omitted in only three years, Honduras failed to make it into the sample in 25 of the 31 years. Similarly, while Botswana appears in the sample for each year, Mozambique does not make the sample in 21 of the years. Similar variation exists in other parts of the world. The full 1,830 observations are reflected in the first, simple multivariate model of table 4 that relates traffic fatalities to per capita income and income inequality without any additional control variables. In the descriptive statistics of table 3 and relatively more complete models of tables 4-7 which do include various additional control variables, the estimating sample size falls to 1,114 as additional observations lacked information on one or more of these control variables. The most common control variables lacking that lead to the sample size reductions were those relating to, as described below, the extent of a country's roadway networks, the number of vehicles in use in a given country, and measures of a country's health care network and educational opportunities. In addition to being discussed below, to make them readily available, all variable definitions and sources are summarized in appendix 1.

The key variables in the analysis relate to a country's annual number of traffic fatalities, its per capita income, and its distribution of income. The only worldwide source for information on traffic fatalities is that provided by the International Road Federation (IRF). The IRF was established in 1948 as a network of more than 80 countries committed to roadway development and safety. Since 1958, the IRF has annually published *World Road Statistics* which is a compilation of road and vehicle statistics such as fatalities, road networks, vehicle production and registration, vehicle and road use taxes, and expenditures on roadways. The data provided in *World Road Statistics* are taken from official sources within national road administrations in more than 185 countries. The *World Road Statistics* series is our source for the number of traffic fatalities per year in each country.[13] We then scale fatalities by a country's population to create traffic fatalities per 100,000 citizens or simply the traffic fatality rate. Data on population is taken from the World Bank's *World Development Indicators*. From this same source, we take GDP per capita, measured in purchasing power parity terms (in constant 2000 US dollars). Based on the discussion in the introduction and the theory sections concerning the expected non-linear relation between per capita income and traffic fatalities, we include GDP per capita in quadratic form in the analysis. Given the relations between income growth, motorization rates, and rates of fatalities per vehicle described above, we anticipate finding the traffic fatality rate rising initially with income until the effect of falling fatalities per vehicle begins to fully offset the effect of increasing motorization after which the income/traffic fatality rate relationship is expected to become negative.

To capture a country's distribution of income, we use the income gini provided by Dollar and Kraay (2002) which, to our knowledge is the most comprehensive source for data on income inequality currently available. This is a common gini coefficient measuring the concentration of incomes between 0 (absolute equality) and 100 (maximum inequality), in percentage terms. While the Dollar and Kraay dataset is drawn from four different sources, the primary source is the UN-WIDER World Income Inequality Database, which substantially extends the earlier, commonly used dataset constructed by Deininger and Squire (1996). An important advantage of the Dollar and Kraay dataset is that it expressly adjusts the gini coefficients for differences in income-based versus consumption-based measures of welfare and for gross versus net income, as recommended by Deininger and Squire (1996). Gini allows for testing of our second primary contention, that an increase in income inequality can be expected to be associated with an increase in a country's traffic fatality rate.

To be sure that our results are not being driven by the omission of other factors which might be

[13] It is important to note that the definition of what constitutes a traffic fatality differs across countries as does the percentage of traffic fatalities reported to the police and thus by governments to the IRF. These issues will be taken into account in the multivariate analysis.

related to traffic fatalities as well as the other independent variables, we introduce a number of other control variables in the more complete models. First are a set of development-related variables. As a measure of educational attainment within a country, we include the secondary school enrollment ratio, taken from *World Development Indicators*. This variable relates the actual number of students of any age enrolled in secondary schools to the total number of persons in the country of secondary school age. Since the ability to take advantage of information relating to traffic safety should be enhanced through education, we expect to find a negative relation between this variable and the traffic fatality rate. Evidence supporting this expectation can be found in Hijar et al (2004) who analyzed road traffic injuries in Mexico and report that a disproportionate share of those injured in traffic accidents had relatively limited formal educations. As a proxy for the extent of a country's health care network, we gather from *World Development Indicators* each country's mortality rate, defined as the annual number of deaths per 1,000 persons. To minimize the possibility of this variable being endogenous, given that the dependent variable is also a count of deaths, we adjust the mortality rate by subtracting those deaths which are traffic-related. Since more well-developed health care networks enhance the survival rates of those injured in traffic accidents, we expect the mortality rate to be positive related to the traffic fatality rate. We also include a measure of a country's vehicle concentration, defined as the number of four–wheeled vehicles (passenger cars, buses, and trucks) in use per person, as reported in *World Road Statistics.* This variable should be positively associated with the traffic fatality rate since increases in the numbers of vehicles driven necessarily lead to increases the likelihoods of both single and multi-vehicle accidents. While vehicle concentration partially gets at the issue of roadway congestion, to fully capture the effect of congestion, we also include a measure of a country's roadway network as given by its kilometers of roadways, taken from *World Road Statistics*, scaled by the country's land area as given by *World Development Indicators*. Since more fully developed roadway networks imply less congestion and thus a reduced likelihood of multi-car accidents, we expect this variable to be negatively related to the traffic fatality rate.

We also include several socio-demographic variables in the analysis. To account for the concentration of a country's population, we include the urban to rural population ratio. This variable is expected to be positively related to the traffic fatality rate since increases in population concentration increase the contact possibility between motor vehicle users and vulnerable road users, as well as that between any two motor vehicles. Two additional variables important in determining a country's traffic fatality rate are the percentage of its population made up of those below the age of 15 and the percentage over the age of 64. Since these two groups tend to have unusually high accident rates, we expect each to be positively related to the traffic fatality rate. Each of these socio-demographic variables is taken from *World Development Indicators*. In an attempt to capture drunk driving, we use a country's adult alcohol consumption per capita, as given by the World Health Organization's *Global Alcohol Database*. To the extent that overall consumption of alcohol is positively related to drunk driving, we expect this variable to exert positive influence on a country's traffic fatality rate.

Finally, to take into account the effect of institutions on traffic fatality rates we include a measure of the rule of law taken from *International Country Risk Guide*. This variable ranges from 0-6 with lower values indicating an environment in which the rule of law is relatively weak. We expect that in a country where the rule of law tends to be weak there will be less attention paid to traffic and vehicle safety regulations both on the part of road users and those designated to enforce such regulations, each of which should tend to increase the country's traffic fatality rate.

4. Multivariate analysis

To rigorously test the predictions of our theoretical model regarding the expected relationships between traffic fatality rates, per capita income and income equality, we estimate the following simple two-way fixed effects model:

$$Traffic\ \ fatality\ rate_{it} = \alpha_0 + \alpha_1\, income\ inequality_{it} + \alpha_2\ \ per\ capita\ income_{it} + \alpha_3\ (per\ capita\ income)^2_{it} + \alpha_4\ X_{it} + \gamma_t + \gamma_i + \varepsilon_{it} \tag{2}$$

where traffic fatality rate is the number of traffic fatalities per 100,000 people for country *i* in year *t*, income inequality is the gini coefficient, per capita income represents GDP per capita, and X_{it} is a vector of additional control variables: health care networks, educational attainment, vehicle congestion, urban to rural ratio, roadway networks, population over 64 years old, population under 15 years old, alcohol consumption per capita, and rule of law. Since all the variables, with the exception of income inequality, vary widely we take the natural log of each in order to reduce the potentially misleading effects of outliers, consequently, all coefficients, other than that of income inequality are interpreted as elasticities.

We use year fixed effects, γ_t, to control for any time-specific effects that shift the level of traffic fatalities for all countries. The most obvious of such effects are the significant technological changes that have lead to numerous safety innovations, such as lap and shoulder harnesses, air bags, more secure auto frames, padded dashboards, and the like, over the period under review. Giving us the second dimension of potential fixed effects, the γ_i represent individual countries, allowing us to capture any unobserved country heterogeneity that is relatively fixed over time, such as road conditions, attitudes about driving, general weather conditions, topography, cultural norms, and so forth. Since our interest is on the partial effects of time-varying covariates, fixed-effects estimation is attractive because it allows any unobserved heterogeneity to be freely correlated with the time-varying covariates. In addition, country fixed effects permit us to take into account differences across countries in terms of a particular country's fatality definition (fatalities on the spot versus within 24 hours versus within three days versus within a month, and the like) and in the percentage of deaths that are reported. To the extent that the degree of under-reporting remains constant over time but varies across countries, the fixed-effects procedure will leave the estimates of the impact of the explanatory variables on the traffic fatality rate unaffected.[14,15]

The first column of table 4 presents a baseline version of the model of equation (2) in which we test the predictions of the theoretical model where only the key variables per capita income, per capita income squared, and income inequality are regressed against the traffic fatality rate. This regression is expanded in column 2 to include all of the control variables noted above, thus, we refer to this as the full model. Both the regressions in columns 1 and 2 use country and year fixed effects. To provide a better understanding of the source or sources of variation in the full model, we also include an OLS estimation of the full model in column 3 and, in columns 4 and 5, regressions which include only year fixed effects and only country fixed effects, respectively. Finally, column 6 shows the results of the estimation of the full model when random effects are assumed. For each regression, a test of the joint significance of the independent variables is significant beyond the .01 level indicating that, taken together, the included variables are powerful in explaining the variation in traffic fatality rates across the sample. Further, it should be noted that all estimations use standard errors that are fully robust with respect to arbitrary heteroskedasticity (Wooldridge, 2003).

Broadly speaking, the results of table 4 provide coefficient estimates that support the predictions of our theoretical model. Specifically, columns 1 and 2, the baseline regression and the full model, show that per capita income has the expected inverted U-shaped relation with traffic fatality rates while income inequality has a positive effect, each of which is statistically significant. These results are also found in the random-effects regression. As discussed above, the positive effect of income inequality on traffic fatality rates arises from several, interrelated sources. For example, when inequality is high, the probability of contact between motor vehicle users and vulnerable road users increases leading to increased traffic fatality

[14] To illustrate, when equation (2) is estimated using fixed effects, the coefficients reflect within-country variation in the traffic fatality rate and its determinants. Multiplying country *i*'s traffic fatality rate by a constant to reflect under-reporting would not change the estimates of the coefficients.

[15] In this aspect, Jacobs et al. (2000) review numerous underreporting studies and found evidence of underreporting rates ranging from 0-26% in high motorized countries and as high as 351% in less motorized countries.

rates. This is especially likely in poorer countries as the number of vulnerable road users declines as per capita income rises. In wealthier countries, the effect of inequality comes about not so much through vulnerable road users but because it causes segments of society with differing incomes to enter the roadways in vehicles of dissimilar size. That is, even in a relatively wealthy country, income variation can be expected to lead those that are relatively poor to drive cars that are, on average, smaller, lacking in the most sophisticated safety equipment, less roadworthy, and thus less safe than the cars driven by their wealthier counterparts. The effect of this is especially pronounced when accidents occur between the relatively rich and poor, as the variance in the size and other safety-related factors of the cars the two groups drive serve to increase the likelihood of fatalities, in comparison to a country with a similar but more equally distributed income. In addition, regardless of the level of income, inequality can be expected to slow investments in public traffic safety interventions further supporting the estimated effect of income inequality.

The second key finding of the regressions in table 4 concerns the link between a country's level of per capita income and traffic fatality rates. Here we find a nonlinear relationship showing that as per capita income rises, the traffic fatality rate also rises up to a threshold level of per capita GDP of $11,454 in the baseline regression, with the opposite relation holding for incomes above this threshold level. This result is consistent with our expectation that traffic fatalities are, at relatively low levels of income, a negative externality of the development process. However, as per capita income surpasses a threshold of about $11,500 a number of personal and collective actions tend to come into play that serve to reverse the rate of traffic fatalities. As discussed above, these might include more required training and greater experience of drivers, greater understanding on the part of drivers and vulnerable road users about how to share roads safely, general improvements in attitudes toward road safety, more fully-developed roadway infrastructures, seat-belt use and other safety-related regulations, vehicle crash prevention activities, traffic-calming interventions, and traffic law enforcement all of which serve to reduce the traffic fatality rate.

The full model reported in column 2 of table 4 as well as the random effects version of column 3 provide generally significant and expected results for the remaining control variables. We find a negative effect on traffic fatality rates of educational attainment suggesting that a better educated population has an enhanced ability to take advantage of information relating to traffic safety. Since a more fully development roadway network reduces the likelihood of crashes, the negative effect found for this variable is expected. Also negative, though not significant is the institution's variable, rule of law. The consistent negative sign of this variable suggests that, at least to a limited extent, the general acceptance of the rule of law likely spills over into a greater degree of acceptance of traffic safety regulation and enforcement. Consistent positive effects are found for the remaining control variables. As a proxy for the lack of development in health care systems, the positive effect of the mortality rate is as predicted. Specifically, controlling for income inequality and income, countries with relatively better health care access suffer fewer traffic fatalities. The result for vehicle concentration suggests that countries in which the number of vehicles per capita increases will be relatively prone to traffic accidents and resulting fatalities. Also as expected, we find that traffic fatality rates tend to rise as a larger share of a country's population are urbanites and as a given population has comparatively large segments in the accident-prone age groups of less than 15 years of age and greater than 64. General per capita alcohol consumption also is found to have a positive effect on traffic fatalities and, as such, may be picking up the effect of drunk driving.

To sum up, as predicted by our theoretical model, the results of the estimation of equation (2) detailed in the baseline, full, and random-effects models support with a reasonably high level of confidence the idea that per capita income and income inequality play key roles in determining a country's traffic fatality rate. Perhaps most importantly, these relations appear quiet insensitive to the addition of alternate measures of development, other socio-demographic variables, and a measure of institutions. To get a better handle on where the variation leading to these results comes from, table 4 also includes three additional variants of the full model. In column 4, the full model is presented when estimated by OLS while in columns 5 and 6, respectively, the full model is presented with only year and only country fixed effects. The key result here is that the primary source of variation in the sample appears to come at the country level. While the result for per capita income remains unchanged, though smaller in degree, regardless of the estimation technique, the coefficient for income inequality, while consistently positive, is only significant when country fixed effects are taken into account suggesting the effects of omitted variables related to unobserved country heterogeneity that is relatively fixed over time. As previously discussed, these might include differences in definitions and reporting of traffic fatalities, road conditions, road maintenance practices, attitudes about driving, general weather conditions, topography, cultural norms, and the like. To the contrary, when year fixed effects are omitted, as in column 5, the results for the key variables remain the same as those reported for the full model.

5. Additional empirical issues

To further evaluate the stability of our results, a variety of alternative estimations of the full model were undertaken, as presented in tables 5-7. First, we consider the sensitivity of our results to outliers. To do so, we estimate the full model using both robust regression and quantile (median) regression techniques. In general terms, robust regression is an iterative technique that starts with OLS estimates, calculates case weights based on absolute residuals, and then iteratively re-estimates the model using those case weights until a pre-set tolerance level is reached. Observations for which the absolute residual is small are assigned case weights that approach unity. Observations with a case weight of unity indicate no detectable outlier problem and thus enter the regression as they would in the simple OLS case. Case weights decline from unity as the absolute residual increases in size. In the extreme, a case weight of zero is assigned to those observations that have very large absolute residuals. So long as an observation has a case weight greater than zero, it is included in the final iterated estimation, in a weighted fashion. Those observations, if any, having case weights equal to zero are essentially dropped from the model. In this way, robust regression provides resistant, or stable, results in the presence of outliers.[16] Column 1 of table 5 reports the robust regression

[16] The specific method we use begins with OLS, then switches to Huber (1973) weights, and finally, for all of the non-zero case weights, finishes the estimation using the biweight function of Beaton and Tukey (1974).

estimates of the full model. This regression is directly comparable to the OLS model of table 4 with the exception that the robust procedure identified 36 outliers which were given case weights of zero. While the robust regression results for a number of the control variables differ from the OLS results, of most importance is the result for income inequality, which, as was the case in the baseline model and other models presented in table 4 that included country fixed effects, is now significant and positive. In addition to the result on income inequality, it is important to note that treating the outliers in the sample leaves the estimated result for per capita income qualitatively unchanged.

To further consider the question of outliers, we re-estimated the full model using the semi-parametric quantile (median) approach. Given the reduced impact of outliers on the median compared to the mean of a dependent variable, the object of this technique is to estimate the median of the dependent variable, conditional on the values of the independent variables. Thus, median regression differs from OLS in that the former fits the median of the dependent variable while the latter centers the variance of the dependent variable around its mean. That is, rather than minimizing the squared deviation from the mean as in OLS, median regression minimizes the absolute deviation around the median of the distribution of the dependent variable. Results using this approach are presented in column 2 of table 5. Once again, when compared with the OLS results, the key difference is that the median regression reports a positive and significant coefficient on income inequality, while preserving the relationship between per capita income and the traffic fatality rate. The results for the control variables are nearly identical, qualitatively, between the robust and median regression models. Given these results, it would seem that far from being driven by outliers, the results reported in table 4 are supported when standard techniques for dealing with outliers are undertaken.

As a second way of considering the stability of our results we estimate the full model using a Generalized Least Squares (GLS) fixed effects technique in which country weights are given by the inverse of the country-specific residual variances, $\omega_i = 1/\hat{\nu}_i$.[17] Along with the estimated coefficients from this model, we report heteroscedasticity-consistent standard errors. The results of this estimation are found in column 4 of table 5 and prove to be completely consistent with those found when using each of the estimating strategies taking advantage of country fixed effects in table 4. Of most importance, the relations between the key independent variables—per capita income and income inequality—and the traffic fatality rate remain the same when using the GLS approach.

Finally, tables 6 and 7 relate to alternative ways of considering the relationship between per capita income and the traffic fatality rate. In table 6, we replace the quadratic version of per capita income with groups of income dummies. Column 1 is based on three income groups while columns 2 and 3 are based on 5 and 7 income groups, respectively. In each case, each group is made-up of an equal share of the country-year observations, the omitted group is the poorest, and two-way fixed effects are used to ease comparison with the full model of table 4. Consequently, the regression in column 1 breaks the sample into thirds, column 2 into fifths, and column 3 into sevenths. While there are minor differences in some of the control variables between these regressions and those of the full model of table 4, it should be noted that this method of addressing the relation between per capita income and the traffic fatality rate leaves the positive relation between income inequality and the traffic fatality rate intact. Further, in each of the cases, one can see the inverted U-shaped relation between per capita income and the traffic fatality rate identified when the quadratic of per capita income is used. Specifically, in each case, as you move through the income groups to higher levels of per capita income, the income dummies indicate a rising fatality rate initially which eventually turns negative (and is significant in the 5 and 7 income grouping cases). Table 7 reports re-estimations of the full model for the 440 country-year observations with per capita incomes less than the sample mean of $8,489 (column 1) and the 674 observations with per capita incomes greater than that mean (column 2). The estimation technique is two-fixed effects in each case. Given that the estimated turning

[17] For details on the specification and estimation of this model see Greene (2003).

point for per capita income identified above occurs at an income level well above the mean value, the regression for those observations with incomes above the mean of per capita income, include that variable in quadratic form while per capita income is entered in linear form for those below the mean. While the control variables tend not to work particularly well in the relatively poor sub-sample of column 2, we do get the expected positive and significant coefficients on per capita income and income inequality. The results are a bit more problematic for the regression of those observations with per capita incomes above $8,489. First, while we do find the coefficient on per capita income to be positive and significant, the coefficient on the square of that variable, while being of the expected negative sign, is not significant at conventional levels (.1). The same is true for the result on income inequality—the coefficient is positive as expected, but not statistically significant. In each case, however, it should be noted that while not rising to conventional levels of significance, there is clearly an indication of the expected outcome as both the coefficients on the square of per capita income and income inequality have t-values of 1.45 or greater. At the same time, it should be noted that the comparatively weak outcome for income inequality may simply accurately reflect the fact that in poor countries inequality causes the relatively poor to enter roadways as pedestrians while in rich countries inequality causes the relatively poor to enter roadways as operators of modest cars. While in each case, as discussed in the introduction, the relatively poor enter the roads in a fashion that leaves them at heightened risk when they encounter their relatively wealthy counterparts, this divergence in mode of entry can reasonably be expected to be more closely correlated with the traffic fatality rate in the poor country case.

5. Concluding remarks

Globally, low- and middle-income countries bear a disproportionate burden of injuries and fatalities from road traffic accidents. Further, within all countries, it is the relatively poor who suffer most. Therefore, our primary objective in this paper is to identify the role of a country's level of development and its distribution of income on its death toll from traffic accidents. To analyze these relationships, we first develop a theoretical model by incorporating accident probabilities between motor vehicles and vulnerable road users as well as between motor vehicles themselves, and multiply these probabilities by the probability that such accidents prove deadly. Interestingly, the model suggests that the relation between per capita income and road traffic fatalities should be non-linear, being positive up to a threshold level of income, then turning negative beyond that level of income. In addition, the model predicts that road traffic fatalities should be a linearly increasing function of income inequality.

We empirically test the theoretical model's predictions by considering, in a two-way fixed effects framework, 1,830 country-year observations of traffic fatalities between 1970 and 2000. Given the standard caveats and the specific caveat concerning the use of aggregate data in this context discussed above, the empirical results strongly support the predictions of the theoretical model. The result for per capita income is not unique. Our contribution to the literature on traffic fatalities concerns the estimated positive, linear relation between inequality and fatality rates. To our knowledge, this relation has not been reported elsewhere.

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TABLE 1

Per capita income, income inequality, and the traffic fatality rate

Panel 1(a). Per capita income and the traffic fatality rate

Variable	Per capita income<8,489 Mean	Per capita income<8,489 Std. Dev.	Per capita income>8,489 Mean	Per capita income>8,489 Std. Dev.	Difference t-test
Traffic fatality rate	13.72	5.44	13.25	8.87	0.47 (1.38)

Panel 1(b). Income inequality and the traffic fatality rate

Variable	Gini>38.2 Mean	Gini>38.2 Std. Dev.	Gini<38.2 Mean	Gini<38.2 Std. Dev.	Difference t-test
Traffic fatality rate	14.19	7.05	12.21	8.91	1.97*** (5.02)

NOTE: t-statistics for differences in means are in parentheses; *** reflects significance at the .01 level.

TABLE 2
Sample countries and the number of years between 1970 and 2000 that each country is missing data on traffic fatalities

Country	Number of years Missing	Country	Number of years Missing
Australia	0	Madagascar	17
Austria	0	Malawi	11
Bangladesh	21	Malaysia	0
Belgium	0	Mauritius	5
Benin	8	Mexico	19
Botswana	0	Morocco	11
Brazil	0	Mozambique	21
Bulgaria	5	Netherlands	1
Cameroon	16	New Zealand	0
Canada	3	Niger	10
Czech Republic	4	Nigeria	16
Chile	0	Norway	0
China	27	Pakistan	1
Colombia	3	Panama	13
Costa Rica	11	Peru	22
Cote D'Ivoire	16	Philippines	9
Cyprus	0	Poland	11
Denmark	0	Portugal	0
Ecuador	15	Romania	13
Egypt	9	Senegal	12
Finland	1	Sierra Leon	17
France	0	Singapore	18
Germany	1	South Africa	2
Greece	0	Spain	1
Honduras	25	Sri Lanka	10
Hong-Kong	1	Swaziland	16
Hungary	0	Sweden	0
India	11	Switzerland	0
Indonesia	13	Thailand	5
Ireland	0	Togo	10
Israel	3	Tunisia	4
Italy	1	Turkey	0
Japan	0	United Kingdom	1
Jordan	9	Uganda	12
Kazakhstan	20	Ukraine	17
Kenya	0	Uruguay	23
Korea	0	United States	1
Latvia	18	Zambia	21
Lesotho	8	Zimbabwe	19
Luxemburg	0		

TABLE 3
Descriptive statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Traffic fatality rate	12.733	6.325	0.187	67.744
Per capita income	8,489.273	7,441.503	243.920	33,139.11
Income inequality	38.217	10.414	16.640	63.700
Health care networks	9.516	3.2461	3.721	27.351
Educational attainment	70.843	32.735	2.020	160.080
Vehicle congestion	0.219	0.197	0.002	0.805
Urban to rural ratio	2.766	4.310	0.095	36.593
Roadway networks	0.739	0.936	0.005	7.108
Population>64	8.793	4.994	2.020	17.920
Population<15	17.36	3.017	10.070	29.220
Alcohol consumption per capita	7.324	5.098	0.010	26.670
Rule of law	4.216	1.630	1	6

Table 4
Correlates of the traffic fatality rate

Variable	(1) Fixed Effects	(2) Fixed Effects	(3) OLS	(4) Fixed Effects	(5) Fixed Effects	(6) Random Effects
Log (per capita income)	2.4332*** (0.106)	2.6827*** (0.213)	1.3660*** (0.309)	2.6314*** (0.223)	1.3404*** (0.326)	2.6060*** 0.209
(Log per capita income)^2	-0.1274*** (0.006)	-0.1365*** (0.0136)	-0.1095*** (0.017)	-0.1570*** (0.012)	-0.1094*** (0.017)	-0.1370*** (0.012)
Income inequality	0.0049** (0.002)	0.0063*** (0.002)	0.0041 (0.003)	0.0043* (0.002)	0.0039 (0.003)	0.0076*** (0.002)
Log (health care networks)		0.2620*** (0.076)	0.3623*** (0.064)	0.3191*** (0.078)	0.3589*** (0.066)	0.2932*** (0.068)
Log(educational attainment)		-0.1305* (0.072)	0.2557*** (0.075)	-0.2353*** (0.075)	0.2626*** (0.078)	-0.1251** (0.059)
Log (vehicle congestion)		0.1606*** (0.056)	0.5470*** (0.049)	0.1198** (0.060)	0.5579*** (0.051)	0.1495*** (0.453)
Log (urban to rural ratio)		0.1779*** (0.051)	0.0179 (0.019)	0.1921*** (0.056)	0.0167 (0.020)	0.0996** (0.041)
Log (roadway networks)		-0.0975** (0.045)	-0.0005 (0.019)	-0.1694*** (0.057)	0.0002 (0.019)	-0.1014*** (0.035)
Log (population>64)		0.4444*** (0.104)	-0.1272 (0.095)	0.4329*** (0.110)	-0.1271 (0.103)	0.1645 (0.104)
Log (population<15)		0.3397*** (0.076)	0.3270*** (0.107)	0.2824*** (0.075)	0.3272*** (0.113)	0.3880*** (0.098)
Log (alcohol consumption per capita)		0.0950** (0.041)	-0.0438** (0.019)	0.1942*** (0.042)	-0.0440** (0.019)	0.0637* (0.034)
Log (rule of law)		-0.0420 (0.041)	0.1217** (0.063)	-0.0878** (0.040)	0.1306* (0.066)	-0.0603 (0.041)
Country FE	Yes	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	No	No	Yes	Yes
F-test[a]	20.73***	26.05***	46.79***	220.29***	17.56***	
Wald X^{2b}						544.38***
Number of Observations	1,830	1,114	1,114	1,114	1,114	1,114

NOTES*:* Standard errors corrected for heteroskedasticity using Huber/White correction in parentheses.
*, **, and *** denotes significance at .1 level, .05 level and .01 level, respectively.
[a,b] Test of the joint significance of the independent variables.

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TABLE 5
Correlates of the traffic fatality rate, alternate specifications

Variable	(1) Robust Regression	(3) Median Regression	(4) Fixed Effects GLS Model
Log (per capita income)	1.4776*** (0.194)	1.3893*** (0.297)	2.6047*** (0.215)
(Log per capita income)^2	-0.1062*** (0.011)	-0.1023*** (0.017)	-0.1556*** (0.012)
Income inequality	0.0126*** (0.002)	0.0081*** (0.003)	0.0044* (0.002)
Log (health care networks)	0.3947*** (0.046)	0.3925*** (0.070)	0.3091*** (0.072)
Log (educational attainment)	0.2558*** (0.045)	0.2146*** (0.070)	-0.2308*** (0.063)
Log (vehicle congestion)	0.3646*** (0.024)	0.3791*** (0.036)	0.1266*** (0.048)
Log (urban to rural ratio)	-0.0570*** (0.012)	-0.0410** (0.018)	0.1971*** (0.057)
Log (roadway networks)	-0.0098 (0.019)	-0.0330* (0.087)	-0.1672*** (0.040)
Log (population>64)	-0.0958* (0.058)	-0.0323 (0.087)	0.4259*** (0.126)
Log (population<15)	0.2716*** (0.108)	0.3013* (0.164)	0.2837*** (0.098)
Log (alcohol consumption per capita)	0.1946 (0.013)	0.0014 (0.019)	0.1897*** (0.037)
Log (rule of law)	0.1214*** (0.037)	0.1530** (0.057)	-0.0742*** (0.028)
Country FE	No	No	Yes
Year FE	No	No	No
F-test[a]	74.56***		1411.44***
Pseudo R^2		0.22	
Number of Observations	1,114	1,114	1,114

NOTES: *, **, and *** denotes significance at .1 level, .05 level and .01 level, respectively.
[a] Test of the joint significance of the independent variables.

TABLE 6
Correlates of the traffic fatality rate, by income group

Variable	(1) Fixed Effects 3 Income Groups	(2) Fixed Effects 5 Income Groups	(3) Fixed Effects 7 Income Groups
Income 2	0.1741*** (0.038)	0.0653 (0.044)	0.0425 (0.048)
Income 3	-0.0008 (0.0552)	0.2006*** (0.063)	0.1768*** (0.065)
Income 4		0.0607 (0.074)	0.2394*** (0.077)
Income 5		-0.1797** (0.085)	0.1192 (0.085)
Income 6			-0.0081 (0.094)
Income 7			-0.2157** (0.100)
Income inequality	0.0086*** (0.003)	0.0069*** (0.007)	0.0054** (0.002)
Log (health care networks)	0.1802** (0.075)	0.2145*** (0.076)	0.2537*** (0.076)
Log (educational attainment)	-0.0251 (0.067)	-0.0461 (0.065)	-0.0102 (0.065)
Log (vehicle congestion)	0.3882*** (0.048)	0.3259*** (0.050)	0.2983*** (0.051)
Log (urban to rural ratio)	0.1665*** (0.064)	0.1146* (0.064)	0.0842 (0.065)
Log (roadway networks)	-0.0171 (0.040)	-0.0517 (0.040)	-0.0639 (0.039)
Log (population>64)	0.2522* (0.132)	0.3198*** (0.130)	0.3267*** (0.130)
Log (population<15)	0.5641*** (0.102)	0.4195*** (0.103)	0.3053*** (0.105)
Log (alcohol consumption per capita)	0.0901** (0.042)	0.0886** (0.042)	0.1085*** (0.042)
Log (rule of law)	-0.0443 (0.044)	-0.0789* (0.044)	-0.0831* (0.044)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
F-test[a]	11.22***	12.32***	12.10***
Number of Observations	1,114	1,114	1,114

NOTES: Standard errors corrected for heteroskedasticity using Huber/White correction in parentheses.
*, **, and *** denotes significance at .1 level, .05 level, and .01 level, respectively.
[a] Test the significance of the independent variables.

TABLE 7
Full model estimations of the sample broken at the mean of per capita income

Variable	(1) Fixed Effects GDPPC>8,489	(2) Fixed Effects GDPPC<8,489
Log (per capita income)	2.5978* (1.544)	0.6482*** (0.092)
(Log per capita income)^2	-0.1252 (0.079)	
Income inequality	0.0029 (0.002)	0.0103** (0.004)
Log (health care networks)	0.3164* (0.172)	0.2391** (0.098)
Log (educational attainment)	-0.3626*** (0.064)	0.1003 (0.098)
Log (vehicle congestion)	0.4664*** (0.087)	0.0165 (0.071)
Log (urban to rural ratio)	-0.1987*** (0.075)	0.0066 (0.098)
Log (roadway networks)	0.0221 (0.041)	-0.118* (0.069)
Log (population>64)	0.2357 (0.164)	-0.0151 (0.215)
Log (population<15)	0.1688** (0.083)	0.1958 (0.216)
Log (alcohol consumption per capita)	0.3129*** (0.083)	0.0979* (0.054)
Log rule of law)	-0.0097 (0.055)	-0.4928 (0.065)
Country FE	Yes	Yes
Year FE	Yes	Yes
F-test[a]	26.89***	5.22***
Number of Observations	440	674

NOTES: Standard errors corrected for heteroskedasticity using Huber/White correction in parentheses.
*, **, and *** denotes significance at .1 level, .05 level and .01 level, respectively.
[a] Test the significance of the independent variables.

APPENDIX 1
Variable definitions and sources

Variable	Definition	Source
Traffic fatality rate	Road traffic fatalities, per 100,000 persons.	IRF *World Road Statistics* yearbooks and World Bank's *World Development Indicators, 2004*
Per capita income	GDP per capita, based on purchasing power parity (PPP).	World Bank's *World Development Indicators, 2004*
Income inequality	An aggregate numerical measure of income inequality ranging from 0 (perfect equality) to 100 (perfect inequality), in percentage terms.	Dollar and Kraay (2000). This dataset is drawn from four sources: UN_WIDER (2000), Deininger and Squire (1996), Ravallion and Chen (2000), and Lundberg and Squire (2000).
Health care networks	Annual number of non-traffic related deaths per 1,000 persons.	IRF *World Road Statistics* yearbooks and World Bank's *World Development Indicators, 2004*
Educational attainment	The ratio of total enrollment, regardless of age, to the population of the age group that typically attends secondary school.	World Bank's *World Development Indicators 2004*
Vehicle concentration	The number of four-wheel vehicles (passenger cars, buses, and trucks) in use, per person.	IRF *World Road Statistics* yearbooks and World Bank's *World Development Indicators, 2004*
Urban to rural ratio	Ratio of urban to rural populations.	World Bank's *World Development Indicators 2004*
Roadway networks	Total kilometers of roadways per square kilometer of land area.	IRF *World Road Statistics* yearbooks and World Bank's *World Development Indicators, 2004*
Population>64	Percentage of population aged 65 and above.	World Bank's *World Development Indicators 2004*
Population<15	Percentage of the population aged14 and below.	World Bank's *World Development Indicators 2004*
Alcohol consumption per capita	Annual alcohol consumption per adult (15 years of age and older) in liters.	*WHO Global Alcohol Database*
Rule of law	Indicator of sound political institutions, a strong court system, and provisions for orderly succession of power.	ICRG dataset, Knack and Keefer (1995)

Figure 1. Traffic fatality rate and per capita income

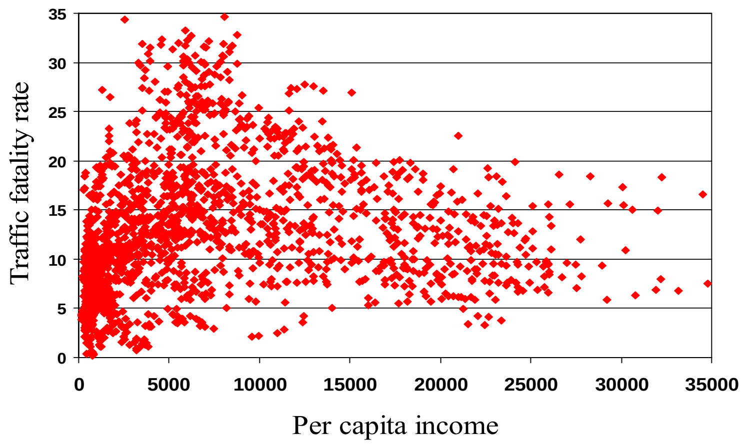

Figure 2. Traffic fatality rate and income inequality