Playing Well with Others:
The Role of Social Capital in Traffic Accident Prevention

Matthew G. Nagler
Department of Economics and Business, The City College of New York, 160 Convent Avenue, New York, NY 10031, USA. Email: mnagler@ccny.cuny.edu

Using data from a panel of 48 U.S. states during 1997-2006, I present evidence that social capital reduces fatal traffic accidents by fostering pro-social behavior among drivers. I estimate simultaneous equation systems that model the incidence of interpersonal interaction-related versus non-interaction-related traffic outcomes, in which variation in endogenous social capital is identified using snow depth. My results show that social capital has a larger relative effect on multi-vehicle and junction-related fatalities and fatal crashes, incidents with respect to which motorist interaction is most critical to outcomes. The findings are robust to alternative specifications and measures of social capital.

Keywords: Social capital; Trust; Highway safety; Panel data; Instrumental variables

JEL: R41; I18; Z13

Social capital has received increased attention in recent years from academic researchers across the social sciences, as well as journalists and policy makers. A considerable volume of work suggests that interpersonal connections, trust, and civic engagement have positive economic impacts [e.g., Helliwell and Putnam 1995, Narayan and Pritchett 1999; Knack 2001; Zak and Knack 2001; Grootaert et al. 2002]. Research also indicates that social capital, measured variously, has beneficial effects on health and well-being.[1] Most of the empirical evidence has centered on statistical associations between social capital and other variables. Definitive causation has been hard to establish [Helliwell 2001], and the putative causal mechanisms involved in social capital's economic and health effects have often been discussed loosely with little hard evidence [Sobel 2002].

As an exception to this, a few recent studies have shown that social connections create economic benefits specifically by acting as collateral to secure transactions and reduce moral hazard [Karlan et al. 2009; Feigenberg et al. 2011; Jackson and Schneider 2011]. These studies have demonstrated that people are motivated to make good on commitments to repay loans and protect property – in effect, fulfilling implicit contracts – so as not to jeopardize their relationships with people they know or, alternatively, risk their standing within close-knit groups (for example, ethnic communities). The studies provide convincing evidence of economic benefits that follow directly from social cohesion in the context of close relationships. But important questions remain unanswered. Does social connectedness provide demonstrable benefits (that is, with demonstrable causality) *beyond* the scope of close relationships? Is it possible to identify behavioral pathways by which social capital propagates to beneficial outcomes in the general context?

This paper contributes evidence on the role of social capital in creating economic benefit in a broader relational context. Specifically, I provide evidence that social capital within a geographically-defined community leads to welfare-enhancing pro-social behavior among people who do not know each other nor share any obvious group connection – people who meet on the roads.

Nagler [forthcoming] previously showed that higher measures of social capital are causally associated with a number of improved highway safety outcomes. The study made use of aggregate measures of interpersonal trust and investment in communal ties to explain variations in the level of traffic fatalities and three other measures of highway safety across a panel of U.S. states over the years 1997-2006. The present paper investigates the mechanism underlying this effect by examining which types of traffic incidents are most strongly influenced by social capital.

I distinguish traffic incidents on two dimensions, intended to indicate whether interpersonal interactions are more or less likely to play a role: by number of vehicles involved (multi-vehicle vs. single vehicle) and by location (junction-related vs. non-junction-related). As motivation for the first distinction, consider Figures 1 through 3. Figure 1 plots the rate of fatalities in multi-vehicle and single-vehicle crashes by U.S. state against survey respondents' average level of agreement with the statement, "Most people are honest." Figure 2 plots the same two incident rate measures against the share of people by state who said they believe "most people can be trusted." Figure 3 plots the two measures against voter turnout by state, a measure of the civic engagement of the populace. A consistent pattern can be observed in the plots. While a strong negative relationship exists between the rate of fatalities in multi-vehicle accidents and each measure of social capital, the relationship between single-vehicle fatalities and social capital appears far more diffuse and less clearly negative. It would seem, observationally, that the role of social capital in explaining single-vehicle fatalities, in which inter-driver interactions are not necessarily a factor, is much less clear its role in explaining multi-vehicle fatalities, where inter-driver interactions are a crucial factor. The hypothesis that social capital promotes safety on the road by fostering pro-social interaction between drivers may be tested by econometrically evaluating whether social capital indeed results in a significantly greater accident-prevention and life-saving effect in interactive incident situations relative to non-interactive situations.

< INSERT FIGURES 1-3 APPROXIMATELY HERE >

To prove causation flowing from social capital to different categories of traffic safety outcomes, I use an identification strategy introduced by Nagler [forthcoming]. The main difficulty with estimating the effect of social capital on highway safety at an aggregate level is that unobserved characteristics of the population may present sources of selection bias. For example, if less conscientious individuals who both eschew civic engagement and drive more recklessly tend to sort disproportionately across states, one might observe higher rates of traffic incidents in states with lower levels of social capital, even in the absence of a causal relationship.

I address the identification problem by exploiting variation in winter snow depth across states as an exogenous source of variation to social capital formation. Snow depth offers a relevant instrument because a snowy climate impacts the long-term movement patterns of individuals. These in turn are relevant to the extent to which individuals form strong ties with each other. For this instrument to be valid, it must also be orthogonal to unobservable determinants of highway risks. As snow accumulation likely contributes directly to the incidence of crashes during the winter, I restrict the dependent variable to safety-related incidents occurring during the summer, thereby satisfying the exclusion criteria.[2] Conceptually, while variation in snow depth plausibly explains variations in social capital from state to state, it does not directly influence the rate of crashes in the summer (non-snow) months of the year. Thus I am able to examine how relative differences in social capital – for which variation comes about by exogenous snow depth variation – influences non-snow related rates of crashes and fatalities. Whereas Nagler [forthcoming] employs this identification strategy to independent two-stage instrumental variables estimation of different traffic incident types (for example, crashes and fatalities, each estimated independently), the present paper uses it to estimate simultaneous equations systems of complementary traffic incident types (that is, interaction-related versus non-interaction-related) via three-stage least squares (3SLS).

I find that instrumented social capital has a larger relative effect, measured in terms both of traffic fatality mitigation and reduction in the number of fatal crashes, in situations involving more than one vehicle and in junction-related situations. The results are robust to the use of different measures of social capital and variations in time- and fixed-effect specifications. The results strongly suggest that social capital positively impacts highway safety through an inter-driver behavioral mechanism, consisting of some form of pro-social behavior or, colloquially, "playing well with others."

Importantly, because this effect occurs on the roads, where pairings of motorists occur to some degree randomly, it provides evidence of a beneficial effect of social capital in a *generalized* context, that is, outside of a close-knit group setting. To better substantiate this claim, I present the results of a separate set of regressions demonstrating social capital's effects on multi-vehicle and junction-related traffic incidents occurring on principal arterial roads versus non-principal-arterial (that is, minor arterial, connector, and local) roads. I do not find social capital's effect on the incident types in question to be greater in the non-principal-arterial context. This supports the notion that social capital's pro-social behavioral effects are not confined to communities of people that know each other, occurring as they do in the most impersonal and randomly-paired driving contexts.

The next section discusses the relationship of social capital to highway safety and advances a pro-social behavior hypothesis of social capital's effects.

Following this is a section that details my empirical strategy, and then a section that describes the data used in the study. The paper then proceeds to present the empirical results and examine robustness to different measures of social capital. After this, I take up the question of whether the measured effects of social capital are generalized effects as opposed to being specific to close relationships. A final summary section concludes the paper.

SOCIAL CAPITAL AND TRAFFIC INCIDENTS: A PRO-SOCIAL BEHAVIOR HYPOTHESIS

Defined by Lynch and Kaplan [1997, p. 307] as a "stock of investments, resources and networks that produce social cohesion, trust, and a willingness to engage in community activities," social capital is typically treated as a multi-faceted phenomenon. According to Harpham et al. [2004], social capital comprises a *structural* component – social networks, connections, and resources – and a *cognitive* component – a set of perceptions and attitudes. The multi-faceted view is associated with a portfolio approach to measurement that uses a combination of structural, investment-oriented indicators, such as organization membership, intensity of volunteer activity, and voter turnout; and attitude-oriented indicators, such as measures of the extent to which people believe others are honest or can be trusted.

Robert D. Putnam [1993; 2000] identifies a number of beneficial effects with social capital's different facets. Networks of social connections between people provide tangible economic effects to the connected persons, such as helping them to find jobs [Putnam 2000, p. 289]. Social networks may also benefit connected individuals through subtle biological and psychological mechanisms, enabling them to fight illness and cope with stresses and psychological traumas more effectively [Putnam 2000, p. 289]. At a collective level, the connectedness of individuals in a community enables them to form stronger political and legal institutions. In environments with greater social capital, people are more engaged in the political process, such that a more responsive government, more effective laws, and a lower rate of political corruption are the result [Putnam 1993; 2000, pp. 338-349].

Beyond these direct benefits of being connected to other people, social capital's cognitive component, consisting of the perceptions and attitudes that are associated with being connected, has putative beneficial effects of its own. People in strong communities, Putnam argues, tend to *trust* – specifically, the people they know well, and more generally, the people they do not know. They also tend to be more trustworthy, and the mutually-reinforcing quality of these two tendencies at a group level embodies what are known as norms of cooperation or norms of generalized reciprocity [Putnam 2000, pp. 134-7]. Group tendencies of trust and trustworthiness, according to Putnam, set in motion an important economically-relevant benefit: they cause people to act in a way that resolves collective action problems more easily. Thus, for example, an individual will take on, at her own cost, an activity that benefits the group, such as using less water in her lawn sprinkler during the summer months, confident that others will do the same [Putnam 2000, p. 288]. Such actions may be categorized variously, depending upon the particular norms they are perceived as relating to, as courtesy (i.e., things one does to fulfill norms of politeness and deference to others) or altruism (i.e., things one does for others out of the goodness of one's heart), among others.

In addition to trust in others' adherence to norms of reciprocity, people in a community with strong ties may have greater confidence that the other members of the community will adhere to a range of recognized codes of behavior. This may induce them to adhere to these codes of behavior more strongly for their own part. The virtuous cycle of adherence and confidence in others' adherence can lead to more effective *coordination* of a range of individual activities, such that individuals in a group or society benefit collectively.

Those individual decisions and actions in the group context, precipitated by social capital, that directly benefit others and thereby provide a general social benefit, may be referred to collectively as “pro-social” behaviors. Other authors than Putnam have pointed out the tendency of social capital to produce pro-social behaviors and consequent economic benefits. Knack and Keefer [1997] contend that norms of cooperation induce people to contribute to public goods and discourage defection in prisonners’ dilemmas. Zak and Knack [2001] argue that in more trusting societies moral hazard poses less of a problem in market transactions, whence individuals are able to spend more time on productive activity and less on investigating potential breaches of trust.

Pro-social behavior provides a logical explanation for why social capital might lead to lower rates of crashes and fatalities on the roads. Whereas non-altruistic drivers consider only their own costs, altruistic drivers would tend to factor in others’ injury and vehicular repair costs when selecting their personal level of driving care. The consequence is that such drivers internalize some or all of the driving externality and increase the average level of care taken on the roads, reducing accidents. Recent reports find aggressive (i.e., discourteous) driving to be a leading cause of accidents and deaths on the road, suggesting the importance of conscientious and considerate behavior in reducing such incidents [AAA Foundation for Traffic Safety 2009; Paleti et al. 2010]. To the extent that social capital leads to altruism and courtesy, it would tend to promote traffic safety.

Social capital’s tendency to promote better coordination among individuals by reinforcing social norms and codes of behavior would also seem likely to have beneficial effects on the roads. Driving is inherently a coordinative activity. It is well-recognized that motorists choose their behavior based on what they observe other motorists doing or what they expect them to do.[3] Safety in many instances depends upon drivers choosing complementary or mutually non-disruptive behaviors, for example, everyone driving on the same side of the road or at approximately the same speed [Lave 1985], or harmonizing with respect to who will enter a non-signalized intersection first [Wilde 1976]. And while the need for coordination relates to simple behaviors for which there are conventions, it also relates to complex discretionary driving behaviors needed to avoid collisions. Since motorists rarely have the opportunity to communicate with each other verbally in advance of risky situations, shared norms of behavior typically govern decisions [Björklund and Åberg 2005]. A range of situations has been recognized (for instance, approaching a yellow light, or approaching a railroad crossing) in which failure of drivers to interpret roadway stimuli consistent with one another can increase the incidence of accidents [Wilde 1976]. Safety requires that motorists trust each other to conform to generally accepted behaviors and interpretations. They must also make a commitment to abide by these norms, that is, to be "trustworthy."

Analysts and scholars have previously recognized that confidence in shared acceptance of behavioral norms might play a role in highway safety. Grjebine [2000] speculated in *Le Monde* that a lower rate of traffic fatalities at the holidays in Norway relative to France had to do with Norwegians having a greater level of acceptance of the social contract. Along similar lines, Helliwell [2003, p. 12] has suggested that highway safety is related to the "extent to which people might feel that traffic and other norms are reliably accepted by other drivers." While the arguments are not explicit, the suggestion is that confidence that behavioral norms are generally strongly accepted by others provides motivation for pro-social behavior by drivers that, in turn, saves lives.

But, while pro-social behavior offers one plausible explanation for social capital's positive effects on the roads, there are alternative explanations. Social capital promotes well-being, and happier people may drive more carefully. Research has shown that individuals with suicidal tendencies engage in high-risk behavior, and that those who have attempted suicide have far higher subsequent mortality rates from all causes, particularly accidents [Holley et al. 1998; Antretter et al. 2009]. In addition, given that social capital promotes the formation of more functional political and legal institutions, it might be expected to promote passage and enforcement of laws that positively impact highway safety. In studies at the U.S. state-level, Loeb [1987], Keeler [1994], and Ruhm [1996] have linked a number of highway safety-related laws, including alcohol taxes and speed limits, to lower rates of fatalities. Anbarci et al. [2006] showed in an international study that lower levels of political corruption at the national level correlate with lower rates of traffic fatalities. They interpret their findings as reflecting the extent to which countries with less corrupt governments more effectively enforce their traffic safety laws.

In light of these competing explanations, if a higher measure of social capital in a region leads to better safety outcomes in that region, how might one ascertain whether facilitation of coordination, and pro-social behavior more generally, is one of the operative mechanisms? My approach will be to use the presence of driver interaction in traffic incidents as an indicator for the role of pro-social behavior.

Clearly not all driving situations involve driver interaction. Driving late at night on an empty highway requires that a motorist pay attention to turns in the road, conditions affecting visibility, and the occasional deer entering the roadway, but not to interacting with other vehicles and their drivers. To differentiate situations based on the amount of interaction they require, I propose two methods of classification. First, one might classify situations by the number of vehicles involved. Situations in which multiple vehicles encounter one another on the road perforce involve interaction. Those situations where only one vehicle is present do not. Another way to classify situations is by location. Certain road locations are more likely to require coordinative activity and other forms of driver interaction than others. Street intersections, for instance, bring motorists together in ways that require them to work together [Lum and Wong 2003]. The same would seem to be true of highway on-ramps, driveway entrances, and left-turn lanes.

One may extrapolate from these two situation definitions to what observed traffic incidents reveal about the role of pro-social behaviors. The occurrence of single vehicle crashes – due to rollovers, loss of vehicular control, collision with the median, and so on – may be ascribed to individual factors such as inattention, as well as road conditions such as darkness, rain, and so forth. Coordination with other motorists, while relevant in certain incidents of this type (consider, for example, a motorist who swerves to avoid another car and then collides with the median), is not necessarily a factor. Neither would other pro-social behaviors, including courtesy and altruism, come into play in single-vehicle crashes. Meanwhile, failure to avoid a multi-vehicle crash involves perforce a failure of coordination and cooperation among drivers, at least at some level. Other factors, such as road conditions, may be critical to the outcome; but the role of coordination, as well as other individual decisions that involve the possibility of pro-social behavior between drivers, is inescapable.

Similarly, crashes occurring at junction locations – that is, in or related to intersections, highway entrance or exit ramps, crossovers (such as left-turn lanes), and driveway access – are more likely to involve failures to coordinate or to behave pro-socially than crashes not occurring at junction locations. While exceptions of both types are possible – for example, a junction crash in which a vehicle veers off the road with no other vehicle near, or a game of "chicken" between two motorists resulting in a collision on a freeway nowhere near an interchange – one may infer the likely role of pro-social behavioral failures from the location of the incident.

These considerations lead to a testable hypothesis. If measurable differences in social capital from one place to another are associated with differences in the rate of traffic incidents to a greater extent in multi-vehicle crashes than in single-vehicle crashes, or at junction locations than at non-junction locations, then social capital is accomplishing its traffic safety benefits, *inter alia*, by facilitating pro-social behavior by drivers.[4]

EMPIRICAL STRATEGY

My empirical strategy for investigating the pro-social behavior hypothesis represents an elaboration on the basic approach of Nagler [forthcoming]. Fatal crashes and traffic fatalities are count variables close to zero: the probability that a given member of the population will be involved in one during a given period is low, and there are a finite number of such incidents. As such, the determination of these incidents is best modeled as a Poisson process; one may appropriately represent this process by the following specification [Keeler 1994]:

$$y_{it} = \exp\left(X_{it}'\beta + \varepsilon_{it}\right) \tag{1}$$

where y_{it} consists of the count of the relevant incidents occurring in state *i* and year *t*, X_{it}' is a corresponding vector of observed characteristics, and ε_{it} consists of unobservable determinants of incidents. A linear estimation model for traffic incidents is derived from equation (1) by taking natural logs of both sides.

My particular specification elaborates on the log version of equation (1) to represent the formation of social capital and its role in *two complementary types* of traffic incidents as follows:

$$\log\left(y_{it}^{a}\right)=\alpha^{a}S_{it}+\sum_{j}\beta_{j}^{a}X_{ijt}+\varepsilon_{it}^{a}$$
$$\log\left(y_{it}^{a'}\right)=\alpha^{a'}S_{it}+\sum_{j}\beta_{j}^{a'}X_{ijt}+\varepsilon_{it}^{a'} \qquad (2)$$
$$S_{it}=\sum_{j}\gamma_{j}X_{ijt}+\xi_{it}$$

Here $k=a,a'$, indexes the type of traffic incident, such that y_{it}^{k} now represents the count of incidents of type k, with corresponding unobservable determinants ε_{it}^{k}. S_{it} represents a measure of social capital, the X_{ijt} are the remaining observed characteristics, and ξ_{it} are unobservable determinants of social capital. I will use this specification to model two pairings of complementary traffic incident types: incidents involving more than one vehicle versus single-vehicle incidents, and junction-related incidents versus non-junction incidents.

The unobservable determinants of complementary types of incidents are likely correlated, thus to estimate equation (2) efficiently one must account for $E\left(\varepsilon_{it}^{a},\varepsilon_{it}^{a'}\right)\neq 0$. Moreover, consistent estimation of equation (2) requires that $E\left(\varepsilon_{it}^{a},\xi_{it}\right)=E\left(\varepsilon_{it}^{a'},\xi_{it}\right)=0$. This is likely to be violated. States with more reckless drivers might well have a different rate of selection into activities of social or civic engagement. In particular, personal tendencies toward courteous driving and civic responsibility are probably correlated. Hence, unobservable differences in the distribution of individuals' characteristics across states influence both the level of social capital and traffic incidents. This biases the estimation of coefficients in the incidents equations in equation (2).

The bias may be eliminated by employing an instrument Z_{it} that is correlated with social capital but otherwise independent of traffic incidents. An appropriate instrument would offer a source of exogenous variation in social capital that approximates the random assignment arising from an experimental process. I employ snow depth. Nagler [forthcoming] provides empirical evidence supporting the conceptual basis for using snow depth as an instrument for social capital – that snow depth affects the long-term movement patterns of individuals, which in turn determines social capital formation. The article finds, using two-stage least squares estimation on a cross-section of states, that average snow depth has a strong positive influence on the percent of people having short commute times, and that the instrumented short commute time-percentage in turn has a strongly significant positive influence on social capital. That article also presents F-statistics for snow depth as an instrumental variable and partial R^2 for the first-stage estimation of a social capital equation employing snow depth as an instrument within a two-stage system. The results show that snow depth has strong explanatory power with respect to social capital.

To be a consistent instrument, snow depth must meet an additional condition, that of being independent of the number of fatal crashes and traffic fatalities. This condition is not likely to be met, because snow tends to make roads less safe for driving. Following Gayer [2004], who also employs snow depth as an instrument in a highway safety regression, I address this problem by restricting my traffic incident measures to fatal crashes and traffic fatalities that occur during the summer months (June, July, and August). That is, in equation (2), I replace the y_{it}^k with $\tilde{y}_{it}^k$, which counts the relevant traffic incidents occurring in state *i* in June, July, or August of year *t*.

The estimated version of the system becomes

$$\begin{aligned}
\log\left(\tilde{y}_{it}^{a}\right) &= \alpha^{a}\hat{S}_{it} + \sum_{j}\beta_{j}^{a}X_{ijt} + \tilde{\varepsilon}_{it}^{a} \\
\log\left(\tilde{y}_{it}^{a'}\right) &= \alpha^{a'}\hat{S}_{it} + \sum_{j}\beta_{j}^{a'}X_{ijt} + \tilde{\varepsilon}_{it}^{a'} \\
S_{it} &= \delta Z_{it} + \sum_{j}\gamma_{j}X_{ijt} + \xi_{it}
\end{aligned} \tag{3}$$

where $\tilde{\varepsilon}_{it}^{k}\left(k=a,a'\right)$ represents the unobservable determinants of incidents of type k occurring in the summer. I estimate equation (3) by three-stage least squares (3SLS), which allows me to account both for the endogeneity of social capital and the relationship of complementary traffic incident types.

Consistent with Gayer's [2004] analysis, whereas $E\left(Z,\varepsilon_{it}^{k}\middle|X_{it}\right)\neq 0$, strict identification of the estimated equation system depends on $E\left(Z,\tilde{\varepsilon}_{it}^{k}\middle|X_{it}\right)=0$. But while the analogous condition is met for Gayer's model, this condition is not met for the present model: snow depth likely affects the rate of traffic incidents in the summer through increased year-round selection into SUVs and other light trucks, something which is not accounted for in the estimated system. However, as shall be observed in the results section, the violation of the exclusion restriction in this model runs counter to snow depth's effect on traffic incidents through social capital: snow depth instrumenting for social capital has a *negative* influence on summer traffic incidents. Thus the effects of vehicle selection actually reinforce identification of the causal effect of social capital.[5]

In the context of equation (3), the pro-social behavior hypothesis is specified as

$$H_0:\alpha^{a}=\alpha^{a'} \text{ vs. } \alpha^{a}>\alpha^{a'} \tag{4}$$

That is, I will test whether the effect of social capital on incidents where driver interaction is expected to be relevant is greater than its effect on incidents where interaction is not expected to be relevant. Note that the interpretation of the test result as indicating that social capital's effect on interaction-related incidents is "more significant" must account for the relative number of interaction-related versus non-interaction-related incidents. A difference in coefficient sizes may simply reflect the extent to which incidents of a certain type are more prevalent in the population. This issue will be treated explicitly in the results section.

DATA

I have compiled count data by state by year for the 48 contiguous United States on the incidence of total fatal crashes (that is, crashes in which at least one person died – hereafter, simply "crashes") and total fatalities in crashes. To conform with my empirical strategy, the data are partitioned two ways. First, I am able to distinguish crashes involving more than one vehicle "in transport" (that is, not legally parked) from crashes involving just one vehicle.[6] Second, I am able to distinguish crashes occurring at a "junction" location from other crashes, where a junction is defined to include locations in or related to intersections and interchanges, highway entrance or exit ramps, crossovers (such as left-turn lanes), railroad grade crossings, and driveway access. All counts relate to the months of June, July, and August only. All traffic event data came from the Fatality Analysis Reporting System (FARS) of the National Highway Traffic Safety Administration (NHTSA) and cover the ten-year period 1997 through 2006.[7]

I measure social capital for the main regressions by the trusting attitudes it creates. Specifically, I use a measure of generalized trust derived from responses to a question in the DDB Life Style Data, which asks respondents whether "most people are honest."[8] Individual responses were reported on a 6-level agree/disagree scale, with "6" representing the greatest level of agreement with the statement. I averaged responses within each state-year using sample weights to obtain the variable for use in the study. Because this variable was characterized by low survey response rates for some smaller states, I used a two-part strategy to ensure a reliable, complete set of state-year averages. First, for five low-count states, I replaced the state-year averages with averages from higher-count adjacent states. Second, I took a 3-year moving average of all state-year observations, weighting by the response count for each state in each year.

Earlier studies have made extensive use of trust measures to represent social capital [Kawachi et al. 2004]. Survey-response measures of generalized trust have been discussed at length in the literature [e.g., Knack and Keefer 1997; Uslaner 2002; Soroka et al. 2006], and there is reasonably good evidence supporting their validity and reliability. Knack and Keefer [1997], for example, refer to evidence that the trust measure from the World Values Survey (WVS) tracks closely with the results of a trust experiment involving recovery of a "lost" wallet, conducted in 1996 in 20 cities selected from 14 western European countries. While the measure I use asks whether most people are honest rather than whether than "most people can be trusted," which is the wording most commonly used (for instance, in the WVS), Putnam [2000, p. 487] observes that responses to the two questions are highly correlated. In the next section of the paper, I will examine the robustness of my results with respect to substituting a measure based on the more common trust question.[9]

My data for snow depth come from the "Surface Summary of the Day" produced by the National Climatic Data Center.[10] This data source offers surface condition data for every weather station in the United States. Following the methodology described by Gayer [2004, p. 111], I based my instrument on average daily snow depth in inches across all weather stations for days in January, February, March, October, November, and December. While I will not present the data here in the interest of space, I can confirm that most of the sample variation in this measure occurs across states, rather than within states over time. This pattern of variation fits well with the decision to use average daily snow depth as an instrument for social capital, for which one expects variation from place to place but stability over time within geographies.

Table 1 presents summary statistics for traffic incidents, social capital, and snow depth.

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RESULTS

Junction-Related vs. Non-Junction-Related Incidents

Let us first consider the effects of social capital on incidents occurring in different locations. I employ a version of equation (3) that incorporates control variables in log form, following previous work on the determinants of traffic incidents by Kopits and Cropper [2005] and Bishai et al. [2006]. Each of the three equations in each estimated system specification controls for real gross state product per capita, vehicle miles traveled per capita, state population, unpaved roads as a percent of local road mileage, gas stations per 1,000 population, population per mile of road (in thousands), percent of population age 65 and over, and the maximum state speed limit. The first two equations in each system employ as dependent variables the log number of junction-related incidents and non-junction-related incidents, respectively. My social capital variable, agreement with "most people are honest," is included with the other covariates in these equations. In the third equation, social capital is the dependent variable; this equation includes as an explanatory variable, in addition to the controls, my measure of average daily snow depth.

I estimate eight specifications in all using 3SLS, four relating to the determinants of fatalities in crashes and four relating to the determinants of crashes. The specifications vary based on the addition of different combinations of a general time trend, year indicators, and a state-specific linear time-trend. Inclusion of these controls should help reduce selection bias, as they will pick up the effects of mean shifts in any unobservable determinants across years, as well as variations in unobservables that occur linearly over time or over time within states.

The results, displayed in Table 2, suggest that social capital reduces crashes and fatalities both at junctions and at non-junction locations. The social capital coefficient estimates are negative in all specifications and highly significant in most specifications. But, while relevant to both types of incidents, social capital appears to have a significantly greater effect with respect to junction-related incidents than non-junction-related incidents. While the significant negative effects of social capital on fatalities and fatal crashes at non-junction locations could reflect one of the several *non*-pro-social-behavior explanations of social capital's safety effects (discussed above in the second section), the presence of greater effects in junction-related incidents directly supports the pro-social behavior hypothesis. The social capital coefficients in the junction-related incident equations range in size from just less than twice as large to more than four times as large as those in the non-junction-related incident equations. A chi-square test finds these differences to be significant at the 5% level in 6 out of 8 runs, and significant at the 10% level in the remaining two runs.

< PLACE TABLE 2 APPROXIMATELY HERE >

However, simply comparing the coefficients fails to account for the relative frequency of incidents of different types. Taking this into account, I find even greater support for the pro-social behavior hypothesis. Table 1 shows that the number of junction-related crashes and fatalities in each state is much smaller on average than the number of corresponding non-junction-related incidents. Thus, even for coefficients of the same size, the influence of social capital would be much larger in percentage terms for junction-related incidents than for non-junction-related incidents.

To understand the overall significance of the difference in social capital's effects, consider the effects of a one-standard-deviation increase in the average level of agreement with the statement, "Most people are honest" – a change of about 5%. The coefficients in model #1 indicate a decline in junction-related fatalities of about 27%, but a decline in non-junction-related fatalities of only 16%. Using the coefficients in model #3, one obtains a larger difference, with declines in junction-related and non-junction-related fatalities of 26% and 7%, respectively. The difference in effects for crashes is similarly large. Using the coefficients in model #5, a one-standard-deviation increase in the honesty variable results in a reduction in junction-related crashes of about 25%, but a reduction in non-junction-related crashes of only 14%. For model #7, the results are 25% and 6%, respectively.

In Table 2, I also present estimation results for the social capital equation. These show a consistently significant positive relationship of average snow depth to my social capital measure. The results here are consistent with the findings of Nagler [forthcoming] that support the use of snow depth as an instrument for social capital.

Multi-Vehicle vs. Single-Vehicle Incidents

Now let us consider social capital's effects on incidents involving different numbers of vehicles. Table 3 presents the results of 3SLS estimation of a set of equation systems identical to those described in the previous subsection, but with the log number of multi-vehicle incidents and single-vehicle incidents as the dependent variables in the first two equations. As before, I estimate eight specifications, four relating to the determinants of fatalities in crashes and four relating to the determinants of crashes; the specifications vary based on the addition of different combinations of a general time trend, year indicators, and a state-specific linear time-trend.

< PLACE TABLE 3 APPROXIMATELY HERE >

The results are quite consistent with those obtained distinguishing incidents based on their relationship to junctions. Social capital reduces the incidence of crashes and fatalities involving more than one vehicle and those involving just one vehicle. Though stricter fixed-effect controls diminish the size and significance of these effects a little, the social capital coefficient estimates in the incident equations are consistently negative and significant. And, again, social capital appears to have a greater influence on incidents in which driver interaction and related behavioral choices are clearly critical to the outcome than on incidents where the role of these is not as clear. The coefficient size differences consistently indicate a larger effect on multi-vehicle incidents. The social capital coefficients in the multi-vehicle-incident and single-vehicle-incident equations are closer to each other in size than were the corresponding coefficients for junction-related relative to non-junction-related incidents. Additionally, the chi-square test results come out significant for size differences in the coefficients in only half the specifications, and at no lower than the 10% critical level; the effects are less significant where stricter fixed-effect controls are used. Table 1 reveals, however, that states have on average about one-third more single-vehicle crashes than multi-vehicle crashes, and about one-fifth more fatalities associated with single-vehicle crashes than with multi-vehicle crashes. Thus, even for coefficients of the same size, the influence of social capital would be larger in percentage terms for multi-vehicle incidents than for single-vehicle incidents. Thus, the results appear to support the pro-social behavior hypothesis.[11]

Consider the effects of a one-standard-deviation difference in the average level of agreement with “Most people are honest.” The coefficients in model #1 indicate a decline in multi-vehicle fatalities of about 24%, but a decline in single-vehicle fatalities of only 16%. Even using the coefficients in model #4, which provide the most conservative reading, one obtains declines in multi-vehicle and single-vehicle fatalities of 15% and 10%, respectively. With respect to effects on the number of crashes, a significantly larger effect of social capital on multi-vehicle incidents is similarly evident for most of the specifications. Based on the coefficients in model #5, a one-standard-deviation increase in the honesty variable results in a reduction in multi-vehicle crashes of about 22%, but a reduction in single-vehicle crashes of only 15%. (With respect to model #7, for which the measured difference in the coefficients is smallest, the results are 13% and 11%, respectively.)

Table 3 also presents the results of estimating the social capital equation in the multi-vehicle-vs.-single-vehicle-incident system. These results are identical to those obtained from estimating this equation as part of the junction-vs.-non-junction-incident system, and they are similarly supportive of the strategy of using snow depth as an instrument.

Different Measures of Social Capital

As a further check on sensitivity to specification choice, I investigate the robustness of my findings to the use of different measures of social capital.

My first alternative variable is an alternate measure of generalized trust, consisting of the percentage of people by state that agree with the statement, "Most people can be trusted."[12] Data for this variable came from the General Social Survey (GSS).[13] One notable limitation of the GSS response data is that they were categorized only by region, not state. To obtain state-level estimates, I adjusted the region values using state averages produced by Robert D. Putnam for the period 1972-1996 based on GSS response data to the same question.[14]

In Table 4, I present the results of 3SLS estimation employing the new variable. Estimation results are shown for each of the two equation systems previously considered: junction-related versus non-junction-related incidents, and multi-vehicle versus single-vehicle incidents. Only results for the traffic incident equations are presented; results for the social capital equation are suppressed. The findings are consistent with those obtained using the honesty variable. Social capital's impact in reducing the incidence of crashes and fatalities is greater in those traffic situations where driver interaction is most clearly relevant to the outcome. Chi-square tests show these differences in effect to be significant in most cases.

< PLACE TABLE 4 APPROXIMATELY HERE >

My second alternative variable is a social capital investment index. The index sums four components: electoral turnout, church attendance, club meeting attendance, and volunteer activity. I choose these components because they cover the three most influential areas of community engagement (described, for example, by Putnam [2000]): political participation, religious participation, and civic participation. Each component is measured by state by year and is standardized to zero mean and unit variance prior to summing.[15] As discussed previously, social capital may be thought of as a stock of various investments in the community and the polis *and* as the set of attitudes that result from these investments. Whereas responses to survey questions that ask whether people are generally honest or can be trusted measure the latter, my index attempts to measure the former.

Table 5 displays the results of employing the social capital investment index in the regression model in place of the honesty variable. While slightly weaker than those presented previously, particularly with respect to the equation system examining relationship to junction, the results remain uniformly consistent with the pro-social behavior hypothesis. Social capital's effects on the rate of fatal crashes and the rate of fatalities in crashes are larger in situations where driver interaction is most clearly relevant to the outcome. Once again, most of the chi-square tests show these size differences to be statistically significant.

< PLACE TABLE 5 APPROXIMATELY HERE >

EVIDENCE OF GENERALIZED EFFECTS

The foregoing analysis has shown that interpersonal connections, trust, and civic engagement within a region lead to a lower incidence of crashes and traffic fatalities, with the effect being greatest for sub-classes of incidents where driver interaction plays a clear role. The findings suggest that social capital fosters life-saving benefits on the roads in part because it promotes pro-social behavior.

But what sort of pro-social behavior is reflected here? My results are open to two interpretations. One possibility is that social capital is fostering beneficial behaviors mainly among people who know each other personally or otherwise have some kind of close relationship to one another. In regions with stronger communal ties, people generally have stronger bonds of trust and shared understanding with the people they know or to whom they have some clear connection (such as members of the same ethnic group). If they were to encounter these people on the roads and recognize them, they might be likely to feel more at ease with them and to have the sense that they share an understanding as fellow drivers. In effect, there would be smoother coordination and a greater motivation to engage in various other pro-social behaviors among such motorists who share a close relationship. The result, taken across the mass of motorists, would be safer driving, on average, and fewer serious accidents.

The other possibility is that social capital is affecting the quality of interaction not just among people who share an explicit relationship, but also among people who do not. In regions with stronger communal ties, people might conceivably develop a stronger sense of generalized trust, feeling they share an understanding with people, at least within some broadly defined geography or community, even if they do not share an explicit group connection with them. Such people might feel more at ease generally when on the roads with all the people they encounter there. The assumption of shared understanding would result in greater courtesy, altruism, and coordination among drivers in general within the region in question, with the result being fewer serious accidents.

To investigate which of these interpretations is the more accurate, I have estimated two separate systems of equations based on equation (3). In the first system, the complementary traffic incident types *a* and *a'* consist of junction-related incidents occurring on principal arterial roads ("PARs") and junction-related incidents occurring on all other roads ("non-PARs"). In the second system, the complementary incident types consist of multi-vehicle incidents occurring on PARs versus those occurring on non-PARs. The Federal Highway Administration defines rural PARs as consisting of routes that are "indicative of substantial statewide or interstate travel." They account for 2 to 4% of total rural road mileage in most states. Urban PARs provide service for traffic "passing through the area" and for "major movements within … urbanized areas … such as between central business districts and outlying residential areas," but in all cases serving "the longest trip desires." These account for between 5 and 10% of total urban road mileage on average [FHWA 2000, II-8 to II-14]. The complement to PARs is the category consisting of minor arterial roads, collectors, and local roads. In rural areas, these roads would generally enable access to small towns and villages and movement within these settlements, as well as access to adjoining land. In urban areas, they would enable access to and movement within neighborhoods.

If social capital is mainly improving safety on the roads by pro-social behavior among people who know each other or share an close-knit-group connection, then one would expect its effects on junction-related and multi-vehicle traffic incidents to be significantly less on PARs, where people are less likely to encounter explicitly connected people and more likely to find people just "passing through" the area. If, on the other hand, the effects are the same or greater on PARs as on all other roads, this would suggest that social capital promotes pro-social behavior among people who do not know each other or share membership in a close-knit group, as well as people who do.

Table 6 presents the results. Only effects on fatalities were considered. In order to preserve observations when logs were taken, I converted “0” observations to “0.01” prior to performing the regressions. As in the core regressions discussed in the previous section, I use 3SLS, employ agreement with “most people are honest” as the social capital variable, and use average daily snow depth as my instrument in the social capital equation. The same control variables and specification variants are employed here as in previous runs, except that vehicle miles traveled per capita and population per mile of road vary by equation so as to be specific to the particular road type accounted for. For example, for the PARs equation, vehicle miles traveled per capita includes only miles traveled on PARs, and population per mile is based only on PAR mileage. In addition, because unpaved roads as a percent of local road mileage does not apply to PARs, it is assumed constant across all observations for PAR fatalities, and so is not included in the PAR equation. To put the results in a relative-size context, I present summary statistics for PAR and non-PAR fatalities in junction-related and multi-vehicle accidents in Table 7.

< PLACE TABLE 6 APPROXIMATELY HERE >

< PLACE TABLE 7 APPROXIMATELY HERE >

In the case of summer multi-vehicle fatalities, the results seem to show, if anything, that social capital has a greater influence on the incidence of fatalities on principal arterial roads than it does on other roads. The coefficients on the honesty variable are consistently larger in the PAR equations than in the non-PAR equations.

In the case of junction-related fatalities, the picture appears more nuanced. Two of the four specifications show larger effects for social capital on fatalities occurring on non-PARs. The coefficients in these cases are slightly more than

50% larger than the corresponding PAR coefficients. (Meanwhile, the coefficient estimates in the other two specifications came out more than twice as large in the PAR equations as in the non-PAR equations.) However, a review of Table 7 shows that states, on average, have a far greater number of junction-related fatalities per summer on non-PARs than on PARs – substantially more than twice as many. Placed in the context of the larger base of fatalities, and considering percentage effects, the coefficient differences actually indicate an effect that is larger in relative significance for PARs than non-PARs across *all four* specifications. Taken together, the results support the proposition that social capital's effects on traffic safety through pro-social behavior are generalized effects rather than relationship-specific effects.

CONCLUSION

Social capital, while positively impacting traffic safety, does so unevenly. Using three-stage least squares and identifying my system using snow depth as an instrument for endogenous social capital, I find that the latter has a significantly more substantial effect on the rate of fatal crashes and traffic fatalities in situations in which interaction among drivers plays a role. For most of my specifications, hypothesis tests indicate significantly larger coefficients on social capital in multi-vehicle incident equations relative to single-vehicle incident equations, and in junction-related incident equations relative to non-junction-related incident equations. When viewed in the context of the relative frequency of non-interaction-related incidents in the population, the relative size of social capital's impact on interaction-related incidents is seen to be even more pronounced.

The results are highly robust. Significant relevant differences in social capital's effects by incident type hold up across different measures of social capital and the inclusion of different fixed effect and time-trend combinations. Overall, a pro-social behavior hypothesis of social capital's effects is strongly supported.

The impacts are not specific to personal relationship and close-knit groups. Social capital's effects on traffic safety in junction-related and multi-vehicle incidents are observed to be no larger on local roads than they are in the impersonal environment of principal arterial roads. Whereas previous studies have indicated relationship-specific mechanisms and effects for social capital, the present results indicate that social capital's effects on traffic safety are, at least in part, generalized effects. Through the mechanism of generalized trust and shared norms, social capital appears to help people to "play well" together even if they do not know each other or share an explicit connection.

The ability to connect social capital with pro-social behavior in the traffic safety arena has important implications. While it is useful to know that social capital saves lives on the road (as demonstrated by Nagler [forthcoming]), having an idea of how this happens is crucial to drawing correct public policy conclusions. Based on this paper's results, it appears that the traffic safety benefits of social capital might be gained by working directly to foster trust and cooperation among drivers. One policy solution may be to augment the technical driver-training curriculum currently taught in secondary schools by including, or integrating more co-equally, precepts related to trust and cooperative driver attitudes. (One might, for instance, emphasize to students that in each of the other vehicles on the road are people like themselves, and that this recognition be transferred to all aspects of daily driving behavior.) Beyond education, a number of additional ways in which public policy can work to create a culture of traffic safety that includes greater trust and coordination are currently under development.[16] The results presented in this paper suggest that approaches along these lines hold considerable promise.

The more general implication that social capital creates at least some of its benefits through a pro-social behavior mechanism has broad policy relevance, in that a number of economic policy problems are related to failure of agents to behave in a pro-social manner. These problems come up at the level of close-knit groups, as studies relating to moral hazard, such as those cited in the introduction, indicate. But they also appear in impersonal contexts, as with respect to the problem of maintaining the quality of shared resources such as platforms and public goods. Targeted policies focused on trust, civic-mindedness, and coordination have the potential to provide benefits ranging from the reduction of upkeep costs at national parks and to enhancing the long-term quality and survival of publicly-beneficial online wikis. More work needs to be done to research and formulate the specifics of such policies.

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APPENDIX: COMPONENTS OF SOCIAL CAPITAL INVESTMENT INDEX

As noted in the text, my social capital investment index variable is the sum of four standardized components:

1. *Electoral Turnout:* I use the state-level turnout rate of the voting eligible population for the highest office election for the year. "Highest office" refers to the presidential election in presidential election years, and either the gubernatorial (if any) or congressional election in other even-numbered years. Data were obtained from the United States Elections Project for even-numbered years in the sample period.[17] To obtain values for odd-numbered years, and to eliminate "seasonality" due to the greater turnout accruing to presidential elections, I set observations equal to an average of the nearest presidential election year turnout and nearest even-numbered non-presidential election year turnout. Where two years were equidistant from the year in question (that is, when setting values for even-numbered years), their values were averaged. This component provides a state-year level measure of the extent to which people are invested in the political process.
2. *Church Attendance:* This component measures the percent of people by state by year who say that they attend church at least once per week. The component is based on responses to a question in the GSS that asked individuals how often they attended church. Responses were recoded to reflect binary attendance on a weekly basis or greater, so that averages across geographies by year using sample weights yield the desired percent measure. As noted previously with respect to the trust variable, the GSS response data were available categorized only by region, not state. Accordingly, I averaged responses by region by year and applied region values to the corresponding states. This component provides a state-year level measure of the extent to which people are invested in their local religious communities.

3. *Club Meeting Attendance:* I use responses to a question in the DDB Life Style Data, which asked how many club meetings the individual attended last year. Calculation follows the same procedure as outlined in the data section for the "most people are honest" variable (prior to standardization). This component provides a state-year level measure of the extent to which people are invested in local secular groups and organizations.
4. *Volunteer Activity:* I use responses to a question in the DDB Life Style Data, which asked how many times the individual volunteered last year. Calculation follows the same procedure as outlined in the data section for the "most people are honest" variable (prior to standardization). This component provides a state-year level measure of the extent to which people are invested in activities that are contribute to the local community.

Notes

1. For a survey relating to health, see Kawachi et al. [2004]; and for evidence on well-being,
2. Gayer's [2004] study of the fatality risks posed by light trucks relative to cars pioneered both the use of snow depth as an instrument (in his case, for vehicle miles traveled by vehicle type) and the use of restriction to summer crashes to ensure validity of the instrument. For further discussion of the validity of snow depth as an instrument, see footnote 5 *infra*.
3. See, for example, Wilde [1976], and the game-theoretic analysis of Pederson [2003].
4. Consistent with this hypothesis is the possibility that altruistic behavior could convert *potential* incidents from multi-vehicle to single-vehicle. For example, a

self-sacrificing driver might act to protect others, swerving to avoid other cars and crashing by himself.

5. Unbiased estimation of equation (3) requires orthogonality of the instrumental variable snow depth to all unobservable determinants of the summer incidents, including variables other than those related to vehicle selection. I have performed several validity checks, including verifying that snow depth is uncorrelated with observable covariates and with a key outcome measure, gross state product per capita, that is likely related to unobserved population characteristics. I have also used interaction of snow depth with gasoline prices to simultaneously evaluate the strength of the instrument and verify its direct orthogonality with summer incidents, following an approach used by Oberholzer-Gee and Strumpf [2007, p. 20]. In the interests of space, the results of these validity tests are not presented in this paper but are available from the author on request. (Gayer [2004], too, has performed a range of validity tests on snow depth as an instrument in models using summer crashes or fatalities as the dependent variable. See his article for details and results.)

6. The National Highway Traffic Safety Administration (NHTSA) considers both vehicles in motion on roadways and those stopped or left on the roadway but not legally parked to be "in transport" for accident accounting purposes. See NHTSA [2004, p. 23].

7. Data are available at http://www-fars.nhtsa.dot.gov/.

8. All DDB Life Style data were provided to me through the generosity of DDB Worldwide Communications, who retain all rights to the data, including copyright. Copyright 1997-2006 by DDB Worldwide Communications.

9. Glaeser et al. [2000] find that responses to the standard trust survey question do a better job of predicting trustworthiness than trust. While interpretation of results based on using a measure of trustworthiness would differ slightly from using a measure of trust, both provide a reasonable representation of the role that

social connectedness plays in highway safety, relative to the conceptualization discussed in the second section.

10. Access is available at http://www.ncdc.noaa.gov/oa/ncdc.html.

11. Similar to the observed effects of social capital at non-junction locations, the significant negative effects of social capital on fatalities and fatal crashes involving a single vehicle might reflect one of several non-pro-social-behavior explanations of social capital's effect on highway safety discussed in the second section.

12. The precise question asks respondents to indicate if they believe "most people can be trusted," or if, instead, it is truer to say that "you can't be too careful."

13. GSS data may be downloaded from http://www.norc.org/GSS+Website/ [Davis and Smith 2006]. Documentation relating to the GSS may be found in the GSS codebook [Davis et al. 2007].

14. See Putnam [2000, p. 290-1]. These data are available on Putnam's *Bowling Alone* website and cover 41 states. For states not covered by Putnam's averages, I used the region-level GSS data without adjustment.

15. Detailed descriptions of the component measures and their data sources are provided in the Appendix.

16. Work in this area is being conducted, for example, by the Center for Health and Safety Culture of the Western Transportation Institute at Montana State University. See http://www.westerntransportationinstitute.org/centers/culture.

17. http://elections.gmu.edu/voter_turnout.htm.

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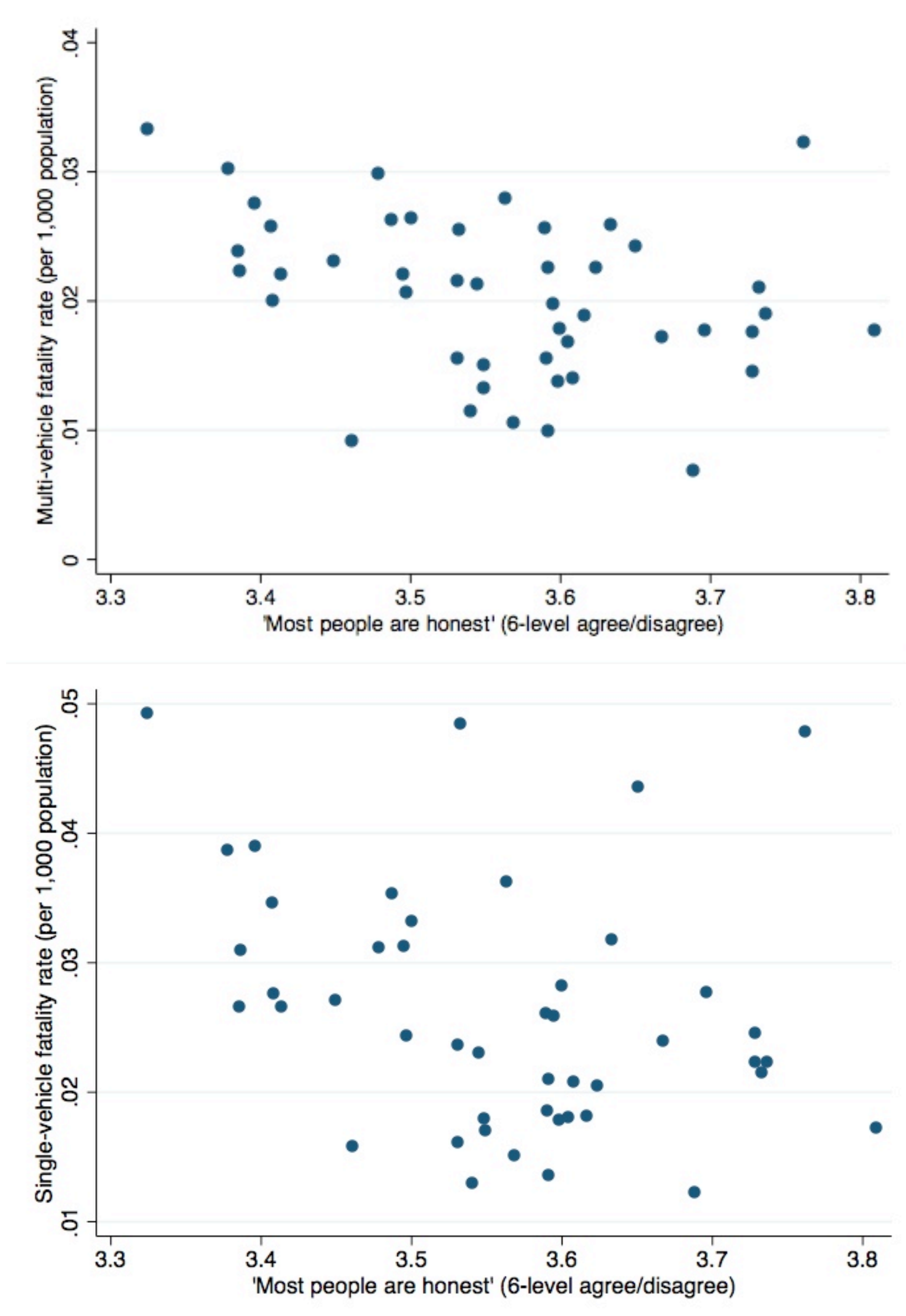

Figure 1. Fatalities in Multi-Vehicle and Single-Vehicle Crashes - Relationship to Believing "Most People Are Honest"

Notes: Each dot represents a state. Plots show averaged data over the 1997-2006 sample period for 46 states. Two outliers with unusually high single-vehicle fatality rates were removed. For data sources, see text.

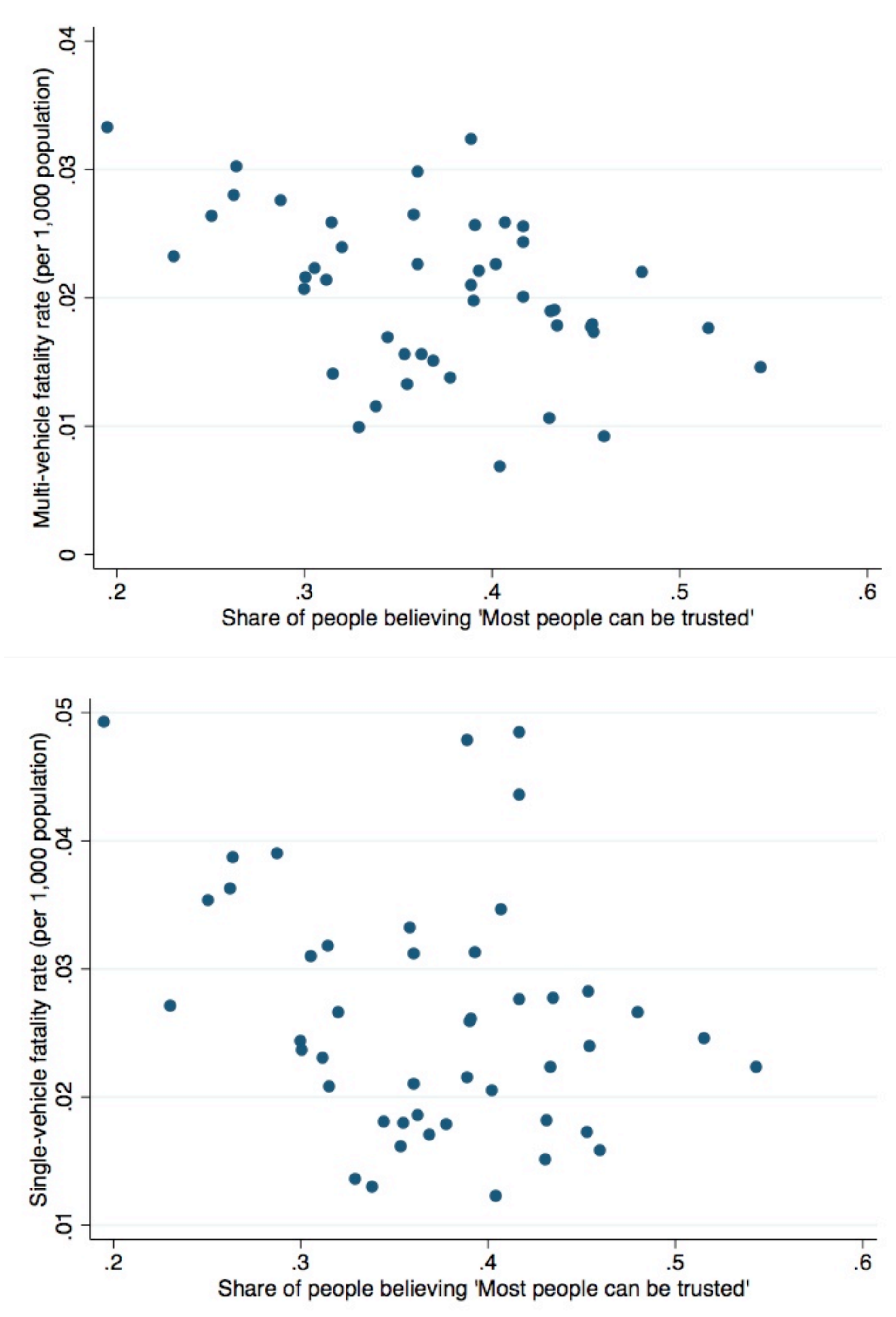

Figure 2. Fatalities in Multi-Vehicle and Single-Vehicle Crashes - Relationship to Trust

Notes: Each dot represents a state. Plots show averaged data over the 1997-2006 sample period for 46 states. Two outliers with unusually high single-vehicle fatality rates were removed. Source for trust data: the *Bowling Alone* website of Robert D. Putnam - see text.

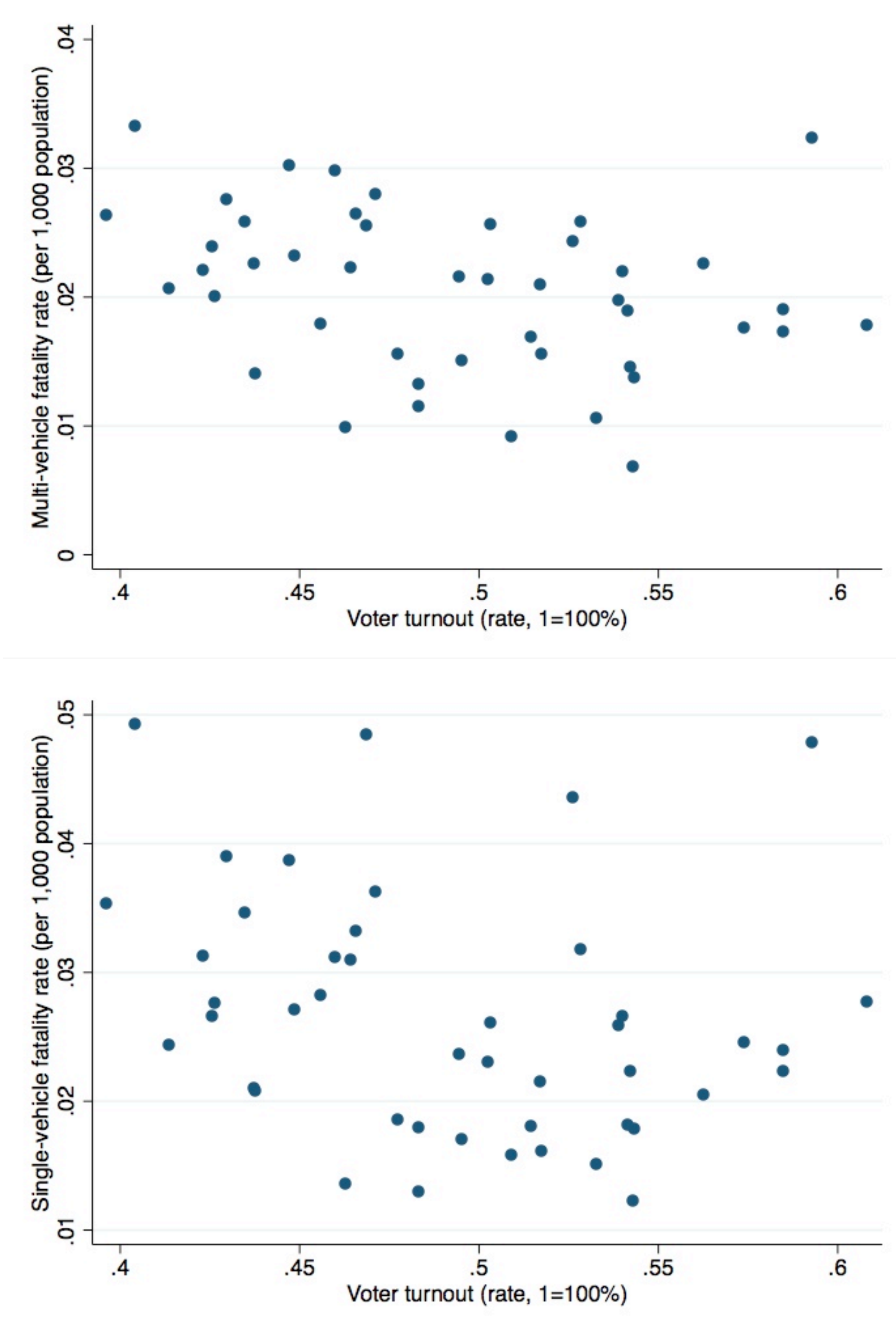

Figure 3. Fatalities in Multi-Vehicle and Single-Vehicle Crashes - Relationship to Voter Turnout

Notes: Each dot represents a state. Plots show averaged data over the 1997-2006 sample period for 45 states. Two outliers with unusually high single-vehicle fatality rates, and one outlier with high turnout, were removed. Source for the voter turnout data: United States Elections Project, http://elections.gmu.edu/voter_turnout.htm.

TABLE 1 - Summary Statistics - Traffic Incidents, Social Capital, and Snow Depth Variables (N=480)

Variable	Mean	St. Dev.	Min.	Max
Summer traffic incidents				
Fatal Crashes				
Multi-vehicle	90.59	82.73	3	435
Single-vehicle	123.30	109.59	8	626
Junction-related	59.81	56.20	1	285
Non-junction-related	154.09	138.11	10	785
Fatalities				
in multi-vehicle crashes	107.17	98.88	4	541
in single-vehicle crashes	132.86	118.41	11	695
in junction-related crashes	66.20	61.88	2	317
in non-junction-related crashes	173.83	157.52	10	919
Social capital				
"Most people are honest" (6-level agree scale)	3.56	0.19	2.84	4.16
Snow depth (in inches)				
Average daily snow depth - Jan., Feb., Mar., Oct., Nov., Dec.	1.33	1.86	0.00	10.90

Notes: Observations in the panel data set consist of a given state in a given year between 1997 and 2006.

TABLE 2 - 3SLS: Effect of Social Capital - Junction-Related Incidents vs. Non-Junction Incidents

	Summer fatalities (log of)				Summer fatal crashes (log of)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Equation 1: junction-related incidents								
Social capital (agree "most people are honest")	-1.686***	-1.562***	-1.589***	-1.383***	-1.549***	-1.430***	-1.486***	-1.273***
	(0.368)	(0.313)	(0.574)	(0.414)	(0.353)	(0.302)	(0.561)	(0.408)
R-squared	0.8651	0.8778	0.9097	0.9212	0.8751	0.8855	0.9130	0.9232
Equation 2: non-junction incidents								
Social capital (agree "most people are honest")	-0.905***	-0.818***	-0.402	-0.443**	-0.821***	-0.743***	-0.336	-0.371*
	(0.246)	(0.210)	(0.262)	(0.211)	(0.237)	(0.204)	(0.251)	(0.202)
R-squared	0.9254	0.9314	0.9738	0.9747	0.9297	0.9348	0.9757	0.9764
Equality of coefficients?	R: 5%	R: 5%	R: 5%	R: 5%	R: 10%	R: 5%	R: 10%	R: 5%
Equation 3: social capital								
Average daily snow depth	0.029***	0.033***	0.022***	0.028***	0.029***	0.033***	0.022***	0.028***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
R-squared	0.3164	0.3936	0.5672	0.6357	0.3164	0.3936	0.5672	0.6357
Time trend	Yes	No	No	No	Yes	No	No	No
Year indicators	No	Yes	No	Yes	No	Yes	No	Yes
State-specific linear time trend	No	No	Yes	Yes	No	No	Yes	Yes

Notes: The dependent variable in Equation 1 consists of the natural log of junction-related fatal crashes or of fatalities in junction-related crashes, as indicated, occurring in the summer months (June, July, and August). The dependent variable in Equation 2 is analogous, but pertains to non-junction incidents. The dependent variable in Equation 3 is the social capital variable representing level of agreement with "most people are honest." Each equation controls for (in log form) real gross state product per capita, vehicle miles traveled per capita, state population, unpaved roads as a percent of local road mileage, gas stations per 1,000 population, population per mile of road (in thousands), percent of population age 65 and over, and the maximum state speed limit. N=480 for all models. "Equality of coefficients?" reports results of the chi-square test for equality of the social capital coefficients in Equations 1 and 2 (R=reject, FTR=fail to reject), with critical level for rejections (5, 10 or 15%).

***Significant at 1% level **Significant at 5% level *Significant at 10% level

TABLE 3 - 3SLS: Effect of Social Capital - Multi-Vehicle Incidents vs. Single-Vehicle Incidents

	Summer fatalities (log of)				Summer fatal crashes (log of)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Equation 1: multi-vehicle incidents								
Social capital (agree "most people are honest")	-1.424***	-1.317***	-0.991**	-0.872***	-1.283***	-1.203***	-0.746*	-0.706**
	(0.303)	(0.255)	(0.410)	(0.303)	(0.290)	(0.247)	(0.385)	(0.293)
R-squared	0.9019	0.9127	0.9497	0.9545	0.9102	0.9180	0.9557	0.9576
Equation 2: single-vehicle incidents								
Social capital (agree "most people are honest")	-0.893***	-0.803***	-0.655**	-0.548**	-0.836***	-0.743***	-0.629**	-0.513**
	(0.238)	(0.204)	(0.285)	(0.223)	(0.229)	(0.196)	(0.277)	(0.216)
R-squared	0.9248	0.9308	0.9661	0.9696	0.9298	0.9352	0.9678	0.9712
Equality of coefficients?	R: 10%	R: 10%	FTR	FTR	R: 15%	R: 10%	FTR	FTR
Equation 3: social capital								
Average daily snow depth	0.029***	0.033***	0.022***	0.028***	0.029***	0.033***	0.022***	0.028***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
R-squared	0.3164	0.3936	0.5672	0.6357	0.3164	0.3936	0.5672	0.6357
Time trend	Yes	No	No	No	Yes	No	No	No
Year indicators	No	Yes	No	Yes	No	Yes	No	Yes
State-specific linear time trend	No	No	Yes	Yes	No	No	Yes	Yes

Notes: The dependent variable in Equation 1 consists of the natural log of multi-vehicle fatal crashes or of fatalities in multi-vehicle crashes, as indicated, occurring in the summer months (June, July, and August). The dependent variable in Equation 2 is analogous, but pertains to single-vehicle incidents. The dependent variable in Equation 3 is the social capital variable representing level of agreement with "most people are honest." Each equation controls for (in log form) real gross state product per capita, vehicle miles traveled per capita, state population, unpaved roads as a percent of local road mileage, gas stations per 1,000 population, population per mile of road (in thousands), percent of population age 65 and over, and the maximum state speed limit. N=480 for all models. "Equality of coefficients?" reports results of the chi-square test for equality of the social capital coefficients in Equations 1 and 2 (R=reject, FTR=fail to reject), with critical level for rejections (5, 10 or 15%).

***Significant at 1% level **Significant at 5% level *Significant at 10% level

TABLE 4 - 3SLS: Effect of Social Capital (Trust) on Traffic Incidents of Different Types

	Summer fatalities (log of)				Summer fatal crashes (log of)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
System 1: Junction-related vs. non-junction incidents								
Equation 1: junction-related incidents								
Social capital (agree "most people can be trusted'	-2.667***	-2.777***	-3.330***	-3.793***	-2.451***	-2.542***	-3.104***	-3.491***
	(0.531)	(0.531)	(1.098)	(1.153)	(0.527)	(0.526)	(1.094)	(1.142)
R-squared	0.8877	0.8885	0.9203	0.9187	0.8890	0.8900	0.9204	0.9199
Equation 2: non-junction incidents								
Social capital (agree "most people can be trusted'	-1.431***	-1.454***	-0.978*	-1.216**	-1.298***	-1.321***	-0.811	-1.019**
	(0.363)	(0.362)	(0.547)	(0.574)	(0.352)	(0.352)	(0.521)	(0.549)
R-squared	0.9348	0.9355	0.9747	0.9751	0.9381	0.9385	0.9767	0.9769
Equality of coefficients?	R: 5%	R: 5%	R: 5%	R: 5%	R: 10%	R: 5%	R: 10%	R: 5%
System 2: Multi-vehicle vs. single-vehicle incidents								
Equation 1: multi-vehicle incidents								
Social capital (agree "most people can be trusted'	-2.252***	-2.341***	-2.064***	-2.392***	-2.030***	-2.138***	-1.558**	-1.937**
	(0.401)	(0.399)	(0.410)	(0.839)	(0.393)	(0.394)	(0.773)	(0.811)
R-squared	0.9314	0.9322	0.9541	0.9538	0.9339	0.9342	0.9575	0.9569
Equation 2: single-vehicle incidents								
Social capital (agree "most people can be trusted'	-1.413***	-1.428***	-1.396**	-1.502**	-1.323***	-1.321***	-1.349**	-1.406**
	(0.368)	(0.367)	(0.576)	(0.606)	(0.356)	(0.356)	(0.555)	(0.584)
R-squared	0.9282	0.9288	0.9697	0.9701	0.9324	0.9329	0.9717	0.9721
Equality of coefficients?	R: 10%	R: 5%	FTR	FTR	R: 15%	R: 10%	FTR	FTR
Time trend	Yes	No	No	No	Yes	No	No	No
Year indicators	No	Yes	No	Yes	No	Yes	No	Yes
State-specific linear time trend	No	No	Yes	Yes	No	No	Yes	Yes

Notes: The dependent variables in Equations 1 and 2 for each system consist of the natural log of fatal crashes or fatalities in crashes, as indicated, pertaining to the category of traffic incidents specified, occurring in the summer months (June, July, and August). The dependent variable in Equation 3 (for which results are not shown) is the social capital variable representing the percent of people agreeing that "most people can be trusted." Each equation controls for (in log form) real gross state product per capita, vehicle miles traveled per capita, state population, unpaved roads as a percent of local road mileage, gas stations per 1,000 population, population per mile of road (in thousands), percent of population age 65 and over, and the maximum state speed limit. Equation 3 also includes average daily snow depth. N=480 for all models. "Equality of coefficients?" reports results of the chi-square test for equality of the social capital coefficients in Equations 1 and 2 (R=reject, FTR=fail to reject), with critical level for rejections (5, 10 or 15%).

***Significant at 1% level **Significant at 5% level *Significant at 10% level

TABLE 5 - 3SLS: Effect of Social Capital (Investment Index) on Traffic Incidents of Different Types

	Summer fatalities (log of)				Summer fatal crashes (log of)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
System 1: Junction-related vs. non-junction incidents								
Equation 1: junction-related incidents								
Social capital investment index	-0.252***	-0.224***	-0.653**	-0.312**	-0.232***	-0.205***	-0.586*	-0.287**
	(0.074)	(0.056)	(0.327)	(0.131)	(0.070)	(0.053)	(0.324)	(0.124)
R-squared	0.7583	0.8093	0.3734	0.8454	0.7833	0.8262	0.4867	0.8605
Equation 2: non-junction incidents								
Social capital investment index	-0.135***	-0.117***	-0.226**	-0.100*	-0.123***	-0.106***	-0.180***	-0.084*
	(0.039)	(0.030)	(0.059)	(0.052)	(0.037)	(0.029)	(0.055)	(0.049)
R-squared	0.9150	0.9327	0.9005	0.9692	0.9226	0.9368	0.9299	0.9732
Equality of coefficients?	R: 10%	R: 10%	FTR	R: 10%	R: 10%	R: 10%	FTR	R: 10%
System 2: Multi-vehicle vs. single-vehicle incidents								
Equation 1: multi-vehicle incidents								
Social capital investment index	-0.213***	-0.189***	-0.234	-0.196**	-0.192***	-0.172***	-0.181	-0.159**
	(0.056)	(0.041)	(0.227)	(0.086)	(0.052)	(0.039)	(0.183)	(0.078)
R-squared	0.8510	0.8888	0.8858	0.9277	0.8694	0.8982	0.9185	0.9410
Equation 2: single-vehicle incidents								
Social capital investment index	-0.133***	-0.115***	-0.138**	-0.123**	-0.125***	-0.106***	-0.141**	-0.116**
	(0.040)	(0.031)	(0.059)	(0.059)	(0.038)	(0.029)	(0.057)	(0.056)
R-squared	0.9044	0.9236	0.9401	0.9572	0.9218	0.9295	0.9415	0.9614
Equality of coefficients?	R: 10%	R: 10%	FTR	FTR	R: 15%	R: 10%	FTR	FTR
Time trend	Yes	No	No	No	Yes	No	No	No
Year indicators	No	Yes	No	Yes	No	Yes	No	Yes
State-specific linear time trend	No	No	Yes	Yes	No	No	Yes	Yes

Notes: The dependent variables in Equations 1 and 2 for each system consist of the natural log of fatal crashes or fatalities in crashes, as indicated, pertaining to the category of traffic incidents specified, occurring in the summer months (June, July, and August). The dependent variable in Equation 3 (for which results are not shown) is an index consisting of the sum of four standardized measures of investment in social capital. Each equation controls for (in log form) real gross state product per capita, vehicle miles traveled per capita, state population, unpaved roads as a percent of local road mileage, gas stations per 1,000 population, population per mile of road (in thousands), percent of population age 65 and over, and the maximum state speed limit. Equation 3 also includes average daily snow depth. N=480 for all models. "Equality of coefficients?" reports results of the chi-square test for equality of the social capital coefficients in Equations 1 and 2 (R=reject, FTR=fail to reject), with critical level for rejections (5, 10 or 15%).

***Significant at 1% level **Significant at 5% level *Significant at 10% level

TABLE 6 - 3SLS: Effect of Social Capital - Fatalities on Principal Arterial Roads vs. Fatalities on Other Roads

	(1)	(2)	(3)	(4)
System 1: Junction-related incidents				
Equation 1: summer fatalities on principal arterial roads (log of)				
Social capital (agree "most people are honest")	-1.904***	-1.731***	-4.820***	-4.207***
	(0.707)	(0.661)	(1.264)	(1.050)
R-squared	0.5862	0.5991	0.5849	0.6405
Equation 2: summer fatalities on other roads (log of)				
Social capital (agree "most people are honest")	-3.097***	-2.689***	-2.174***	-1.949***
	(0.390)	(0.342)	(0.462)	(0.393)
R-squared	0.6010	0.6833	0.8346	0.8635
System 2: Multi-vehicle incidents				
Equation 1: summer fatalities on principal arterial roads (log of)				
Social capital (agree "most people are honest")	-0.858***	-0.882***	-1.731***	-1.803***
	(0.290)	(0.271)	(0.500)	(0.413)
R-squared	0.8354	0.8397	0.8622	0.8702
Equation 2: summer fatalities on other roads (log of)				
Social capital (agree "most people are honest")	-0.191	-0.515**	-0.302	-1.245***
	(0.272)	(0.248)	(0.365)	(0.341)
R-squared	0.9028	0.9024	0.9378	0.9248
Time trend	Yes	No	No	No
Year indicators	No	Yes	No	Yes
State-specific linear time trend	No	No	Yes	Yes

Notes: The dependent variable in Equation 1 for each system consists of the natural log of fatalities in crashes on principal arterial roads ("PARs"), as indicated, occurring in the summer months (June, July, and August). The dependent variable in Equation 2 is analogous, but pertains to fatalities occurring on roads other than PARs. The dependent variable in Equation 3 (for which results are not shown) is the social capital variable representing level of agreement with "most people are honest." Equation 1 controls for (in log form) real gross state product per capita, vehicle miles traveled per capita (PARs only), state population, gas stations per 1,000 population, population per mile of PAR (in thousands), percent of population age 65 and over, and the maximum state speed limit. Equations 2 and 3 use the same controls, but with vehicle miles traveled per capita and population per mile of road pertaining to the road class appropriate to each equation (roads other than PARs for Equation 2, all roads for Equation 3); also unpaved roads as a percent of local road mileage is included in these two equations as an additional control. Equation 3 also includes average daily snow depth. N=480 for all models.

***Significant at 1% level **Significant at 5% level *Significant at 10% level

TABLE 7 - Summary Statistics - Fatalities on Principal Arterial Roads and on Other Roads (N=480)

Variable	Mean	St. Dev.	Min.	Max
Junction-related fatalities (summer)				
Principal Arterial Roads	27.68	29.16	0.01*	174
Other Roads	70.91	77.26	1	471
Multi-vehicle fatalities (summer)				
Principal Arterial Roads	50.92	51.57	2	277
Other Roads	56.24	50.81	1	280

Notes: Observations in the panel data set consist of a given state in a given year between 1997 and 2006.
* "0" observations were converted to "0.01" to preserve observations when logs are taken. See text.