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ABSTRACT

Does Social Capital Matter? A Study of Hit-and-Run in US Counties

We investigate the relationship between social capital and the decision to flee after a fatal road accident. This event is unplanned, and the decision is taken under great emotional distress and time pressure, thus providing a test of whether social capital matters for behaviour in extreme conditions. We merge data from the universe of fatality accidents involving pedestrians in the US over the period 2000–2018 with a unique dataset on social capital measures at the county level. Using within-state-year variation, our results show that one standard deviation increase in social capital is associated with a reduction in the probability of hit-and-run of around 10.5%. The causal interpretation of this evidence is supported by a number of falsification tests based on differences in social capital endowment between the county where the accident occurs and the county where the driver resides, as well as by the IV approach proposed by Lewbel (2012). Our findings show the importance of social capital in a new context, suggesting a broad impact on pro-social behaviour and adding to the positive returns of promoting civic norms.

JEL Classification: Z13, D91, K42, R41

Keywords: social capital, crime, hit-and-run, road accidents

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1. INTRODUCTION

Social (or civic) capital can be defined as "those persistent and shared values and beliefs that help a group overcome the free rider problem in the pursuit of socially valuable activities" (Guiso, Sapienza, and Zingales, 2011). In this paper, we study the role of social capital in the decision to flee after a fatal road accident. This decision is taken under great emotional distress and time pressure, following an unplanned and dramatic event. Finding a role for social capital within these extreme conditions represents a new test of the importance of social capital in guiding behaviour, highlighting how it functions even in a fast, instinctive, and emotional setting, or "System 1" in the language of Kahneman (2011).

We contribute to the strand of research analysing whether pro-social attitudes matter in extreme and high-pressure situations (see, for instance, Frey et al., 2010; Frey et al., 2011; Elinder and Erixson, 2012; Sach and Whynes, 2012; Savage, 2013; Savage, 2016). Furthermore, we offer new insights about the impact of social capital on socio-economic outcomes and the heterogeneity of such effects.[1] Hit-and-run road accidents also represent a relevant context in which to study the role of social capital because they are an important phenomenon. According to the AAA (American Automobile Association) Foundation for Traffic Safety, more than one hit-and-run crash happens every minute in the US. At the same time, in 2015, these types of accident were responsible for 1,819 fatalities (5.1% of the total fatalities in road accidents) and 138,500 serious injuries (5.9%), with a stable increase in recent years.[2] Twenty-one percent of pedestrian deaths in 2019 occurred in hit-and-run crashes, for a total of 1,290 victims.[3]

[1] Over the last decades, the literature has stressed the central role of social capital in the functioning of communities (Putnam, 1995; Putnam, 2000; Fukuyama, 1995) and in economic prosperity (see Durlauf and Fafchamps, 2005, for a review of the economics literature). Social capital is associated with higher economic (Tabellini, 2010) and financial development (Guiso et al., 2004), higher and more equal incomes (Knack and Keefer, 1997), higher political accountability (Nannicini et al., 2013), positive health outcomes (Folland, 2007; Xue et al., 2020), fewer Covid-19 cases per capita (Barrios et al., 2021; Bartscher et al., 2021; Durante et al., 2021), and lower crime rates (Lederman et al., 2002; Buonanno et al., 2009). For the impact of the profound social capital heterogeneity that characterises the US, see, for instance, Putnam (1995) and Alesina and La Ferrara (2000).

[2] See https://aaafoundation.org/hit-and-run-crashes-prevalence-contributing-factors-and-countermeasures/.

[3] Source: https://www.iihs.org/topics/fatality-statistics/detail/pedestrians.

In our empirical analysis, we merge 2000–2018 data from the universe of fatal road accidents in the US – retrieved from the Fatality Accident Reporting System (FARS) – with a unique dataset on social capital measures at the county level coming from The Geography of Social Capital in America (2018) project. We focus on accidents that involve pedestrians – representing 59.3% of all hit-and-run accidents – because in these cases the car and the driver usually report negligible damages, and therefore the driver is not forced to stay. Using a number of variables that capture different dimensions of social capital, we find a robust negative association with the probability to flee after a crash.

This relationship could be driven by extrinsic or intrinsic motivation. As to the former, social capital improves civic engagement, informal social control and law enforcement which, in turn, increases the probability of punishment (Sampson, 1988; Buonanno et al., 2009; Ferrer, 2010; Akçomak and Ter Weel, 2012). Furthermore, in areas characterized by high social capital, reputation is important for social acceptance (Williams and Sickles, 2002). In such a context, people are more likely to punish those who violate social norms and do not cooperate (Williams and Sickles, 2002; Akçomak and Ter Weel, 2012); committing a crime might lead to a loss of social network and force the perpetrator outside the community, therefore increasing the economic cost of detection.

Concerning intrinsic motivations, when social capital is high, individuals may have internalized a sense of duty that increases the moral cost of crime. As an example, in the experimental studies by Cohn et al. (2019) and Tannenbaum et al. (2020), generalized morality – a propensity to follow norms of appropriate behaviours toward strangers beyond family, kinship or social group (Tabellini, 2008; Enke, 2019) – increases the reporting of lost wallets. In a similar vein, the literature investigating the determinants of tax evasion has shown that "tax morality" is affected not only by the cost of punishment, but also by social norms and networks (see, for instance, Frey 1997).

In our empirical analysis, we find evidence that both mechanisms are at play. In particular, the likelihood of detection after a hit-and-run is indeed higher in communities with stronger social capital. Moreover, drivers appear to be responsive to the social capital of their county of residence rather than that of the county where the accident happens, when these two locations differ, suggesting that they have internalized norms of behavior.

A potential concern for our analysis is that the relationship between social capital and hit-and-run could be non-causal. Reverse causality is unlikely to be an issue, given that social capital is usually considered a slow-moving variable with deep historical roots (Putnam et al., 1994; Fukuyama, 1995; Guiso et al., 2008). Moreover, while hit-and-run road accidents are dramatic events that might have an impact on the community, they are far less common than other violent crimes that can shape people's mentality (e.g., in the period we consider, there are on average 1,945 hit-and-runs per year vis-à-vis 16,425 murders and 139,815 rapes in 2019).[4]

Omitted variables represent instead a potential threat. In our regressions we control for a rich set of socio-economic characteristics at the county level, such as GDP per capita, unemployment rate, share of blacks. Nevertheless, omitted variables at the county level might indeed affect both the level of social capital and the likelihood of hit-and-run. For instance, urban features may have an impact on social capital by favouring social interaction, and they may also have an impact on hit-and-run, for instance, by making the possibility of fleeing more complicated from a logistical point of view. If this were indeed the case, then we would expect the negative relationship between social capital and the likelihood of fleeing to be the same irrespective of whether the driver is a local or not. If, instead, the relationship we observe at the county level is causal, then we would expect to see a stronger relationship for local drivers than for those who are not local. To deal with this problem, we perform different falsification tests. Our results show that the magnitude of the effect of social capital on the likelihood of fleeing is higher in relative terms on local streets – more frequented by local drivers – than on other roads. Similarly, by exploiting the ZIP code of the driver when known, we show a

[4]Source: https://ucr.fbi.gov/crime-in-the-u.s/2019/crime-in-the-u.s.-2019/topic-pages/violent-crime, accessed on October 21, 2021.

negative and statistically significant relationship between the probability of fleeing and local social capital only for local drivers and not for those who are out-of-county. These findings suggest that location-specific features are not driving the correlation between our two variables of interest, thus corroborating a causal nexus. Finally, we implement the IV approach based on the heteroscedasticity of the error term that has been proposed by Lewbel (2012). The results support the appropriateness of the analysis.

The remaining of this paper is organised as follows: Section 2 describes the data and provides descriptive statistics, Section 3 presents the econometric methodology and results. In Section 4, we address the causality of the effect and investigate some potential channels, while Section 5 offers conclusions.

2. DATA AND DESCRIPTIVE STATISTICS

2.1 Data

Data about fatal accidents involving pedestrians come from the Fatality Accident Reporting System (FARS), a surveillance system operated by the US Department of Transportation (DOT)'s National Highway Traffic Safety Administration (NHTSA). Specifically, the authorities report to this system each motor vehicle collision that occurred on public roadways with one or more fatalities within 30 days of that collision. The FARS data make it possible to define the picture of the accident in terms of location, hour, the number of participants and their characteristics, type of vehicles involved, weather condition, road type and so on.[5] The main variable of interest for this investigation, "HitRun", refers to "cases where a vehicle is a contact vehicle in the crash and does not stop to render aid (this can include drivers who flee the scene on foot)". Around 18% of fatal accidents involving pedestrians

[5] See the Fatality Analysis Reporting System: https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars.

are hit-and-run, a number that is rather stable during the period analyzed. Data on drivers' characteristics such as age, sex, alcohol use, previous license suspension and so on, are available only for those drivers who did not flee or who did flee but have been subsequently identified. Note that the share of identified drivers is 48%.[6]

Regarding social capital, in the literature there are different approaches to its measurement, as social capital is a multifaceted concept (Dasgupta and Serageldin, 2000; Paldam, 2000; Christoforou, 2013). Conceptually, social capital has been associated, for instance, with trust towards other people and institutions, and firm performance (Fukuyama, 1995; Glaeser et al., 2000; Guiso et al., 2008; Akçomak and Ter Weel, 2009; Lins et al., 2017; Stiglitz et al. 2018, Chapter 10); membership in groups, networks and voluntary associations (Putnam et al., 1994; Alesina and La Ferrara, 2002; Sobel, 2002); membership and trust (Lochner et al. 2003; Vincens et al., 2018); membership, trust, and norms of reciprocity (Putnam, 2000; Bigoni et al., 2016). Operationally, higher voter turnout and association density are hypothesised to capture civic involvement and participation in community decision making, while voluntary donations capture the strength of intermediate social structures (e.g., Putnam et al., 1994; Putnam, 2000; Cartocci, 2007; Buonanno et al., 2009). Guiso et al. (2004) suggest using voluntary blood donations as an indicator of civic engagement, as the latter is higher when people care more for each other.

In this study, we exploit the social capital indicators provided by "The Geography of Social Capital in America" (2018) project (employed, among others, by Ding et al., 2020; Borgonovi et al., 2021; Milosh et al., 2021).[7] An important feature of this indicator is that it is at the county-level. In

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[6] If the driver is classified as a hit-and-run driver, but there is information on the driver (for instance: sex, age), we conclude that s/he has been identified by the authorities. We do not know whether the driver has reported him- or herself voluntarily to the police sometime after the accident, or has been identified due to police investigation.

[7] For detailed information on this data, refer to https://www.jec.senate.gov/public/index.cfm/republicans/2018/4/the-geography-of-social-capital-in-america.

particular, the social capital index is a proxy that aggregates information on four sub-indexes: (1) family unity, based, for instance, on the data on marital status or births out of wedlock; (2) community health, based on the data on non-profits, volunteering, civic participation and so on; (3) institutional health, based on the data on voter turnout, trust and confidence in institutions, mail-back response rates for the census; (4) collective efficacy, based on the data on violent crime. A higher score implies higher social capital.[8] The social capital indicator is also available at the state level in an extensive form. Beyond the previously mentioned sub-indexes, the state-level index is also composed of the following additional sub-indicators: (5) family interaction, based, for example, on data about daily activities with children; (6) social support, based on data about the number of close friends, trust and interaction with neighbours; (7) philanthropic health, based on data about the share of people reporting donations to charitable groups. Table A8 in the Appendix offers a comprehensive description of these additional state-level sub-indexes.

Finally, we collect from the Census Bureau and the US Bureau of Economic Analysis data at the county or state level on socio-economic variables such as GDP per capita, total population and unemployment rate. The share of Catholics is retrieved from the ARDA (Association of Religious Data Archive),[9] while information on health facilities is collected from the Area Health Resources Files (AHRF).[10]

2.2 Descriptive Statistics

Table 1 reports a detailed description and the main summary statistics of the variables used in the econometric analysis. Between 2000 and 2018 in the US, there have been 118,688 road accidents involving pedestrians with a share of hit-and-run of around 18%, which in absolute terms amount to 21,363

[8] See Table A7 in the Appendix for details on the variables and sources employed to define the index and the sub-indexes at the county level.

[9] For further details, see: https://www.thearda.com/archive/browse.asp.

[10] See: https://data.hrsa.gov/topics/health-workforce/ahrf.

accidents. The dependent variable in the main econometric analysis (HITRUN) is a dummy equal to 1 if the driver fled the crash scene. In the case of hit-and-run, 48% of drivers are identified after leaving the scene of the accident.[11]

We have standardized the overall social capital index and the four sub-indexes to make results easier to interpret so that they all have mean 0 and standard deviation 1. Table A1, in the Appendix, shows the correlation matrix, from which it emerges that, while the different indexes of social capital usually have a positive correlation with each other, they are not collinear.

As control variables, we use a set of dummies to account for road and accident characteristics such as the place where the accident occurred (LOCALSTREET or URBAN area), light (DAILYLIGHT) and weather (CLEAR_WEATHER) conditions, road characteristics (HIGHSPLIM – for speed limits over 50 mph – and TWOWAY), and HOLIDAY. According to the literature on hit-and-run (Solnick and Hemenway, 1994, 1995; Johnson, 1997; Tay et al., 2008, 2009; MacLeod et al., 2012), these variables influence the choice to flee or stay, because, for instance, they affect the probability of identification. Indeed, a crash during rain and wind, under poor lighting, or in a rural area might induce drivers to flee as it is less likely to be identified by witnesses. Alcohol or drug consumption are important determinants as well since they alter the perception of risk and, in the case of culpability, could aggravate the severity of the penalty. Some of the variables above, e.g., HOLIDAY, capture differential consumption patterns over time, and we also include a dummy variable equal to 1 (DRY) if the county is dry.[12]

Socio-economic features at the county level include the unemployment rate (UNRATE), the real GDP per capita (RGDPPC), the hospital density (HOSPITAL), the share of Catholics (SHARE_CATH),

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[11] It is worth mentioning that the number of observations for the variable IDENTIFIED is slightly lower than 21,363, because in the case of 451 drivers we are unable to retrieve information on whether or not the driver has been identified.

[12] In the US, a dry county is a county whose local government forbids the sale of any kind of alcoholic beverage. Some prohibit off-premises sale, some prohibit on-premises sale, and some prohibit both. Several dry counties exist across the US, mostly in the South.

and the share of black people (SHARE_BLACK). Macroeconomic factors are related to poverty, criminality and security on the road (i.e. use of surveillance cameras) which might influence the probability of fleeing. The healthcare system affects the chances of survival after a crash, thus having an impact on the likelihood of the accident actually being fatal and, thus, being included in the dataset. The share of Catholics could matter because of differences in moral attitudes (e.g., sense of guilt) which may affect the decision to leave the scene of the crash. Furthermore, in areas with a higher proportion of black people, greater fear of authorities may reduce the likelihood of witnesses coming forward, which in turn affects the chance to flee undetected. We also include a dummy equal to 1 if the county borders Mexico (MEX_BORDER), as having an accident close to the Mexican border might facilitate escape from the authorities. Finally, in some specifications, we also control for characteristics of the victim, such as gender (MALE_PED), age (AGE_PED), and ethnicity (WHITE_PED).

The share of hit-and-run is higher at night (between midnight and 4.00 am), during the weekend, on local streets and in urban areas (see Table 2).

[Table 1 and 2]

In Figure 1 and Figure 2, we visually inspect the relationship between social capital and pedestrian hit-and-run crashes.[13] As we can see from Figure 1, the higher social capital level is registered in the West North Central census division, the northern part of the Mountain division and the Pacific division. A higher level of social capital also appears in Wisconsin, Illinois and the New England division.

[Figure 1]

Looking at Figure 2, the lowest percentages of hit-and-run are in the West North Central division, part of New England and the northern part of the Mountain division. Similarly, many counties present

[13] Figures A1 to A4, in the Appendix, report the maps for the social capital sub-indexes.

low hit-and-run incidence in the northern area of the Pacific and West South-Central divisions. On the contrary, higher percentages of hit-and-run are found in the southern counties of the West and South regions. Comparing Figures 1 and 2, there seems to be an inverse relationship between the share of hit-and-run in pedestrian accidents and social capital.

Note that, in any case, these regional differences are not relevant for the econometric analysis, as we include state-year fixed effects.

[Figure 2]

Finally, before moving to the econometric analysis, Figure 3 plots the social capital and hit-and-run at the county level (see Figures A5-A8 in the Appendix for the same with the sub-indexes of social capital). Here, we see a negative correlation between these two variables (r = -0.13). Note that in counties with a low population, there may be very few fatal accidents involving pedestrians, even over the relatively long time period we consider. Therefore, there is a mass around “round” shares like 0%, 33%, 50% and so on. See Figures A9 and A10 in the Appendix for a plot of the number of accidents and the share of hit-and-run by county. Notice that in the econometric analysis, the unit of observation is the single accident, so counties with no crashes involving pedestrians over the time period we consider is not an issue.

[Figure 3]

3. ECONOMETRIC MODEL AND RESULTS

3.1 Preliminary Analysis

For a first glance at the relationship between social capital and hit-and-run, we start from the aggregate state level. Specifically, we estimate a model in which the dependent variable is the percentage of hit-and-run in a state during the whole period (2000–2018). Given the proportional nature of the dependent variable, we rely on a fractional logit regression (Papke and Wooldridge, 1996). The main variable of interest is the social capital indicator at the state level (and its sub-indexes). We control for the following state-level variables: GDP per capita, population density, unemployment rate, the maximum prison sentence for hit-and-run crashes and the extent of insurance coverage.[14] According to Table 3, the social capital endowment at the state level is always negatively correlated with the percentage of hit-and-run, the result being statistically significant for most social capital measures employed. The value of the coefficient in column (1), for instance, implies that one SD increase in the social capital index is associated with a 1.55 percentage point decrease in the share of hit-and-run accidents. Considering that, in the US, the average share of hit-and-run when using the 51 states as a unit of observation is around 17%, the magnitude is economically significant. To better explore the relationship between hit-and-run accidents and social capital, we move to an econometric analysis at the micro-level.

[Table 3]

3.2 Econometric Model

The key hypothesis we want to test is whether and to what extent the social capital endowment, measured at the *county* level, affects the likelihood of fleeing after a fatal accident involving a pedestrian during the period 2000–2018. To this aim, we estimate the following logit model:

$$Prob(HITRUN_i = 1|X) =$$
$$F(\beta_0 + \beta_1 SOCCAP_c + \phi X_i + \varphi Z_c + \sum_{h=1}^{23} \gamma_h \, HOUR_h + \sum_{d=1}^{6} \gamma_d \, DAY_d +$$
$$\sum_{m=1}^{11} \omega_m \, MONTH_m + \sum_{t=2000}^{2017} \sum_{s=1}^{50} \alpha_{ts} \, YEAR_t * STATE_s \,) \qquad (1)$$

[14] Descriptive statistics of the variables used in this estimation are reported in Table A2, while Table A3 shows the correlation matrix.

The dependent variable is a dummy equal to 1 if the accident *i* is a hit-and-run: that is, if the driver flees from the crash scene. The key regressor of the analysis is the overall social capital index (SOC-CAP), or its sub-indexes, in the county *c* where the accident takes place. The vector X of control variables includes dummies capturing the characteristics of the place where the accident occurs (local street or urban area), lighting (DAILYLIGHT) and weather (CLEAR_WEATHER) conditions, public holidays (HOLIDAY), two-lane roads (TWOWAY) and a speed limit over 50 mph (HIGH-SPLIM). Besides, we add a vector of control variables Z accounting for socio-economic features at the county level: unemployment rate (UNRATE), real GDP per capita (RGDPPC), hospital density (HOSPITAL), share of Catholics (SHARE_CATH), share of black people (SHARE_BLACK), dummy variables equal to 1 if the county is dry (DRY) and if the county borders Mexico (MEX_BOR-DER). Lastly, we add dummy variables to control for time and space fixed effects (hour of the day, day of the week, month of the year, and the interaction between year and state). Besides capturing any level differences across states, including year-state fixed effects allows for differential dynamics across states in the likelihood of fleeing. This controls for any change that may occur at the state level in the period under consideration: for example, legislative changes in penalties.

As a robustness check, we further add to the specification some characteristics of accident victims such as sex, age (and its square) and race, information that is available only for a subset of accidents (around 90,000 out of around 109,000). This may be relevant if the probability of fleeing depends on the characteristics of the victim. For instance, according to Solnick and Hemenway (1995), the probability of fleeing is lower when the victims are young or older than 65 years old.

3.3 Results

Table 4a reports the results of the baseline regression. Column 1 includes the overall social capital index (SOCCAP) while, in Columns 2 to 5, we replace the main indicator with the four sub-indexes (COLL_EFF, FAMILY_UNITY, COMM_HEALTH and INST_HEALTH). The level of social capital has a negative and robust association with the probability of fleeing; COMM_HEALTH being the only exception with a negative but insignificant coefficient. Looking at Column 1, one standard deviation increase in SOCCAP is associated with a reduction in the probability of hit-and-run of around 10.5% (that is, a decrease of 0.019 percentage points over a baseline of 0.185).[15]

[Table 4a]

As a robustness check, in Table 4b we add variables related to the victims of the accident. The number of observations drops, but coefficients are still significant and even larger in absolute terms. However, this derives from the different sample size rather than from the inclusion of new variables.[16] Indeed, in Table A6 in the Appendix we use the sample of Table 4b, excluding the variables related to the victims, and we find results very similar to Table 4b in terms of magnitude of the marginal effect.[17] Therefore, our results are robust to the inclusion of these additional variables.

[Table 4b]

4. CAUSALITY AND CHANNELS

4.1 Falsification tests

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[15] In Table A4 in the Appendix, we also report the coefficients for the control variables. These are in line with the literature: hit-and-run appears more likely to occur in local streets and urban areas, during holidays, and on two-way roads. By contrast, there is a lower likelihood to flee after the crash during good weather conditions and in daylight. Concerning county-level features, the unemployment rate, GDP per capita, the share of Catholics and the share of blacks positively affect the probability of running away. When we instead exclude from the specification all the control variables included in Table 4a (with the exception of the time of day, days of the week, month, and year*state dummies) the value of the coefficient related to SOCCAP is -0.038 (s.e. 0.002).

[16] Table A5 in the Appendix also reports the control variables. Concerning victims' features, sex does not appear to influence the choice to leave the scene of the crash; age has a non-linear effect in that it is positive until the age of 46 and negative afterwards, while hitting a white pedestrian reduces the likelihood of fleeing.

[17] The variable that reduces the sample size is WHITE_PED. Excluding this variable from the specification, the sample size remains almost the same, as do the marginal effects.

As mentioned in the introduction, the negative correlation between social capital and hit-and-run does not necessarily imply a causal link. Even if we have exploited variation within state-year, allowing also for differential dynamics of hit-and-run across states, there might still be some omitted variables at the county level affecting both social capital and hit-and-run. For instance, some urban features (such as the design of neighbourhoods, e.g., high vs. low density) may have an impact on social capital by favouring social interaction (Leyden, 2003) as well as on hit-and-run by making it more difficult to flee. If this were the case, we would expect the negative relationship between social capital and the likelihood of fleeing to be the same, irrespective of whether the driver is local or not. If, instead, the relationship we observe at the county level is causal, then we would expect to see a stronger relationship for local drivers than for non-locals. When local drivers have an accident in their own neighbourhood, they are aware of the level of social capital that affects the degree of social control and the probability of being punished. On the contrary, this information might be unknown to non-local drivers.

We perform this test by distinguishing between local and non-local drivers using two different strategies, with a trade-off between quantity and quality of information. The first strategy favours the former and the second one the latter. With the first strategy, we exploit the fact that drivers on local streets are more likely to be local. The advantage here is that the information about the street is available for all accidents, but the disadvantage is that we do not know if a specific driver was a resident in the same county. [18]

[18] Indeed, if we consider accidents for which we have information on drivers' ZIP code, 19% of those occurring on local streets involve drivers from another county, while on highways and interstates this figure is 38% (a difference that is statistically significant). Note that we have information for the ZIP code of the driver in almost 89% of observations. Even assuming an extreme case in which all non-identified drivers on local streets are out-of-county drivers, and all non-identified drivers on non-local streets are resident drivers, it is still the case that the likelihood of an out-of-county driver is lower on local streets (28% vs 35%).

A second strategy is based on the ZIP code of the driver. This has the advantage of clearly distinguishing between local and non-local drivers for each accident, but the disadvantage is that we lack this information for around half of hit-and-run accidents, where the driver is not identified. This second approach is potentially affected by selection bias, since drivers from other counties may be more or less likely to be identified. Note, however, that the share of identified drivers is nearly identical on local (47.88%) and non-local (47.96%) streets (see middle panel of Table 2), suggesting that this may not be a major issue.

To implement the first strategy, in Table 5 we estimate Equation (1) splitting the sample into accidents occurring on local streets (Columns 1 to 5), interstates and state highways (Columns 6 to 10). Results show that the marginal effect of social capital is higher on local streets than on other roads. Focusing on Columns 1 and 6, one standard deviation increase in social capital reduces the likelihood of hit-and-run by 13% on local streets and 5.6% on non-local streets (considering that 21% of drivers flee from local roads compared to the around 16% from other streets), the difference between the two coefficients being statistically significant (p-value = 0.000). This result is confirmed by using COLL_EFF and FAMILY_UNITY sub-indexes. On the contrary, COMM_HEALTH is never significant, while INST_HEALTH shows a negative and significant coefficient only in the *other street* sub-sample, but is not significantly different from the corresponding coefficient in the local street sub-sample (Column 5).

[Table 5]

To implement the second strategy, in Table 6 we estimate Equation (1) by splitting the sample into accidents where the identified driver resides in the county (Columns 1-5) and accidents where the driver is from outside of the county (Columns 6-10). The effect of social capital is negative and statistically significant only in the subsample involving *resident* drivers. The community health sub-index represents an exception, being positive, but only weakly significant, in the *resident* sub-sample.

The results from these two different strategies suggest that the effect of social capital on hit-and-run is indeed stronger for local drivers.

[Table 6]

To delve deeper into this issue, in Table 7a we restrict the analysis to out-of-county drivers and use the social capital of the county of residence instead of that of the accident. One may worry that drivers are mostly from similar counties in terms of social capital (e.g., because of spatial proximity). When we consider this subsample, however, the scatterplot between the social capital in the county of the accident vs. county of residence (Figure A11 in the Appendix) shows only a weakly positive correlation ($r = 0.27$), implying that there is enough variation to disentangle the impact of the two.[19] Table 7a confirms the negative relationship between social capital and the likelihood of fleeing.

[Table 7a]

Finally, in Table 7b, we use both measures and see how the likelihood of fleeing has a stronger relationship, both in terms of statistical significance and in terms of the magnitude of the coefficient, with the social capital characterizing the county of origin rather than the county of the accident. This evidence supports the hypothesis that people respond more strongly to the social capital endowment of the context where they live than to the social capital of the county where the accident took place.

[Table 7b]

Overall, the evidence presented in this section suggests that omitted variables at the county level are not behind the correlation, thus supporting a causal interpretation of the link between social capital and the likelihood of fleeing after an accident.

4.2 Instrumental Variable Approach

[19] See Figures A12-A15 in the Appendix for the same with the sub-indexes of social capital.

To give further support to our previous finding, we adopt an instrumentation strategy based on the Lewbel (2012) approach. Specifically, when it is difficult or impossible to find valid (external) instruments, this approach enables the identification of structural parameters in regression models with endogenous variables by exploiting the heteroscedasticity of the error term. Stated differently, the Lewbel approach allows the construction of instruments based on information about the heteroscedasticity of the error term. The greater the degree of heteroscedasticity in the structural equation error process, the higher will be the correlation between the generated instruments and the endogenous variables.[20] This approach has also been applied in cases, as in this paper, where the dependent variable is dichotomous, e.g., in the implementation of Umberger et al. (2015) and Banerjee et al. (2017). To justify the use of this methodology, we first test the assumption of heteroscedasticity in the error term; the Breusch-Pagan/Cook-Weisberg χ^2 is sufficiently large to reject the null hypothesis of homoscedasticity. Also, the Hansen J statistic, used to test the validity of the overidentifying restriction, supports the validity of our instrumentation strategy by failing to reject the null hypothesis that all instruments are valid. The estimates reported in Table 8 confirm our main results. Moreover, it is important to note that the endogeneity test reported at the bottom of Table 8 is never statistically significant (except in Column 5 at a 10% level), so that the null hypothesis of exogeneity of the instrumented variables cannot be rejected, supporting the appropriateness of the previous analysis.[21]

[TABLE 8]

4.3 Potential channels

As mentioned in the introduction, a possible channel behind the relationship between social capital and the probability of fleeing, related to extrinsic motivation, is that higher social capital at the local

[20] See Lewbel (2012) for a detailed explanation of this approach.

[21] Due to computational issues, we include in the specification state and year fixed effects rather than their interaction.

level could induce a higher probability of identification, for instance because witnesses are more likely to come forward. In order to investigate this aspect, we restrict the analysis to the subsample of hit-and-run accidents and estimate the probability of being identified after fleeing; therefore, the dependent variable is a dummy equal to 1 if the driver has been identified by the authorities, 0 otherwise. This allows us to ascertain whether, in counties characterized by higher social capital, there is indeed a higher probability of being identified after fleeing.

Results in Table 9 show that in counties with higher social capital, the probability of identification is higher; one SD increase in social capital corresponds to approximately a 3 percentage-point increase in the probability of identification, which is sizeable if one considers that around half of the people who fled after the accident were identified. This finding implies that social capital might increase the productivity and efficiency of the authorities and, as a consequence, increase the probability of punishment.

If one considers that local drivers are more likely to be aware of this, then we would expect this effect to be stronger on local streets. Paralleling the analysis conducted above, in Table 10 we split the sample into local vs. non-local streets, confirming that indeed the impact is stronger in the case of local streets.[22]

[Tables 9 and 10]

Concerning intrinsic motivations, one should recall that the evidence presented in Table 7b shows that what matters is social capital in the county of residence rather than in the county where the accident took place. Thus, drivers appear to "bring with them" their social capital endowment, suggesting that an internalized sense of duty may indeed also play a role in explaining the impact of social capital on the likelihood of fleeing.

[22] For obvious reasons, we cannot consider, as done in the second strategy of Section 4.1, only identified drivers when looking at the likelihood of being identified.

6. CONCLUDING REMARKS

In this study we document a negative relationship between social capital endowment and pedestrian hit-and-run road accidents. Our results are robust to different specifications and falsification tests; factoring whether the accident occurs in local areas, or using information about the driver's residence, we offer some evidence supporting a causal interpretation of the correlation between the two variables of interest.

In communities with high social capital, better formal and informal social control reduces anonymity, strengthens social norms, and improves the enforcement of the law. Furthermore, committing a crime in such contexts implies higher expected social sanctions. Finally, social capital might reduce hit-and-run by promoting social norms of reciprocity, a sense of duty, pro-social behaviour, and cooperation.

The literature has shown the importance of social capital for a variety of outcomes. What we show is that social capital matters also for a decision taken under great emotional distress and time pressure, thus pointing to a role of social capital in guiding instinctive behaviour – or "System 1" according to the classification by Kahneman (2011). Interventions targeted to promote civic norms and pro-social behaviour could thus have a beneficial impact across a wide range of domains.

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TABLE 1 - Description and summary statistics of the variables used in the estimations

VARIABLE	DESCRIPTION	Mean	StdD	Min	Max	Obs
HITRUN	Dummy = 1 if the driver run after the accident	0.18	0.39	0	1	118,688
IDENTIFIED	Dummy = 1 if the driver is identified after leaving the scene of the accident	0.48	0.50	0	1	20,912
SOCCAP	Social Capital Index	0	1	-3.79	3.86	118,408
COLL_EFF	Collective Efficacy Sub-Index (see table A4)	0	1	-5.92	1.74	118,240
FAMILY_UNITY	Family Unity Sub-Index (see table A4)	0	1	-5.59	3.51	118,490
COMM_HEALTH	Community Health Sub-Index (see table A4)	0	1	-1.49	12.82	118,688
INST_HEALTH	Institutional Health Sub-Index (see table A4)	0	1	-4.29	3.51	118,606
LOCALSTREET	Dummy = 1 if the accident occurs in local streets (see table notes)	0.46	0.50	0	1	116,772
URBAN	Dummy = 1 if the accident occurs in urban area (see table notes)	0.59	0.49	0	1	118,688
DAYLYLIGHT	Dummy = 1 for accident occurred in daily light conditions	0.29	0.45	0	1	118,688
CLEARWEATHER	Dummy = 1 for accident occurred during good weather condition	0.81	0.39	0	1	118,688
HIGHSPLIM	Dummy = 1 for speed limit higher than 50 miles	0.33	0.47	0	1	118,688
HOLIDAY	Dummy = 1 for accident occurred during holidays	0.030	0.160	0	1	118,688
TWOWAY	Dummy = 1 for accident occurred on a twoway road type	0.49	0.50	0	1	117,132
UNRATE	County unemployment rate	6.18	2.52	1.20	28.90	118,614
SHARE_CATH	Share of Catholics - County level	0.20	0.14	0.00	0.94	117,534
HOSPITAL	Hospital Density: number of hospital in the county over county surface (sq.miles)	0.03	0.08	0.00	0.83	115,176
RGDPPC	County real gross domestic product per capita (in thousand of dollars)	54.69	36.31	5.92	1551.00	116,925
SHARE_BLACK	Share of black people - County level	0.154	0.144	0	1	118,688
DRY	Dummy = 1if the county is dry	0.01	0.08	0	1	118,688
MEX_BORDER	Dummy = 1 if the county borders with Mexico	0.03	0.17	0	1	118,500
MALE_PED	Dummy = 1 if the victim is male	0.723	0.447	0	1	118,515
AGE_PED	Age of the victim	45.01	21.03	0	104	118,106
WHITE_PED	Dummy = 1 if the victim is white	0.73	0.44	0	1	97,943

Notes: the social capital measures (SOCCAP, COLL_EFF, FAMILY_UNITY, COMM_HEALTH, INST_HEALTH) are defined at county level. See Table A4 for a detailed description. As a LOCALSTREET we consider: township, municipality, frontage road and county road. Urban areas are defined according to FHWA-approved adjusted Census boundaries of small urban and urbanized areas.

TABLE 2 - Descriptive Statistics of accidents involving pedestrians.

	Total accidents	hit-and-run	% hit-and-run
	118,688	21,932	18.48
Region			
Northeast	17,777	2,853	16.05
Midwest	17,199	3,318	19.29
South	52,455	9,543	18.19
West	31,257	6,218	19.89
Time of day			
Midnight–3:59 am	16,522	5,766	34.90
4:00–7:59 am	15,435	2,860	18.53
8:00–11:59 am	9,739	770	7.91
Noon–3:59 pm	11,896	888	7.46
4:00–7:59 pm	28,635	3,686	12.87
8:00–11:59 pm	35,840	7,567	21.11
Period of week			
Weekday	70,698	10,877	15.39
Weekend	47,990	11,055	23.04
Season			
Winter	30,785	5,427	17.63
Spring	26,151	4,829	18.47
Summer	27,414	5,534	20.19
Autumn	34,338	6,142	17.89
Light condition			
Daylight	34,577	3,040	8.79
No Daylight	84,111	18,892	22.46
Weather Condition			
Clear Weather	95,847	17,608	18.37
No Clear Weather	22,841	4,324	18.93
Population Density			
Rural	48,069	8,287	17.24
Urban	70,619	13,645	19.32
Type of street			
Highway - Interstate	62,637	9,920	15.84
Local street	54,135	11,595	21.42
Speed limit (mph)			
<55 mph	79,724	15,236	19.11
>= 55 mph	38,964	6,696	17.19
Driver's Residence			
County of the crash	75,251	7,747	10.29
No-County of the crash	30,837	2,391	7.75
	Total hit-and-run	**Driver identified**	**% of identification**
	20,912	10,006	47.85
Type of street			
Highway - Interstate	9,515	4,563	47.96
Local street	11,000	5,267	47.88
	Total Accidents with driver identified	**Resident Driver**	**% of Resident Driver**
	106,088	75,251	70.93
Type of street			
Highway - Interstate	56,841	35,468	62.40
Local street	47,605	38,388	80.64

Note: authors' elaboration on FARS data.

TABLE 3 - Estimation Results: US Macroanalysis (Fractional Logit model)

	1	2	3	4	5	6	7	8
SOCCAP	-0.0155***							
	(0.005)							
FAMILY_UNITY		-0.0091						
		(0.006)						
FAM_INTERACTION			-0.0106					
			(0.007)					
SOCIALSUPPORT				-0.0131***				
				(0.005)				
COMM_HEALTH					-0.0126			
					(0.008)			
INST_HEALTH						-0.0097**		
						(0.005)		
COLL_EFF							-0.0195***	
							(0.007)	
PHILANTROPHIC_HEALTH								-0.0116**
								(0.005)
LRGDPPC	0.0761**	0.0764***	0.0729**	0.0545*	0.0710**	0.0721**	0.0526*	0.0808**
	(0.031)	*(0.029)*	*(0.032)*	*(0.029)*	*(0.033)*	*(0.031)*	*(0.03)*	*(0.033)*
DENSITY	-0.0047	-0.0079*	-0.0029	-0.0026	0.0018	-0.0032	-0.0108*	-0.0044
	(0.004)	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*	*(0.006)*	*(0.005)*
UNRATE	0.0054	0.0100*	0.0094**	0.0068	0.0091**	0.0095*	0.0075	0.0098**
	(0.005)	*(0.005)*	*(0.004)*	*(0.005)*	*(0.004)*	*(0.005)*	*(0.005)*	*(0.005)*
PRISON_SENTENCE	0.001	0.0008	0.0011	0.0008	0.0009	0.0013*	0.0007	0.001
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*
INSURANCE_COV	-0.0023	-0.0029	-0.0029	-0.0019	-0.0037	-0.0028	-0.0027	-0.0033
	(0.652)	*(0.584)*	*(0.569)*	*(0.735)*	*(0.475)*	*(0.618)*	*(0.603)*	*(0.528)*
Observations	51	51	51	51	51	51	51	51
R2	0.004	0.003	0.004	0.004	0.004	0.004	0.004	0.004

Notes: for the description of variables see Table A2. The dependent variable is always PERC_HITRUN. Results are expressed as marginal effects on the percentage of Hit-and-Run. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. The standard errors reported in parentheses are corrected for heteroskedasticity and clustering of the residuals at the state level.

TABLE 4a - Estimation results: US Microanalysis (Logit model)

	1	*2*	*3*	*4*	*5*
SOCCAP	-0.0189***				
	(0.003)				
COLL_EFF		-0.0142***			
		(0.003)			
FAMILY_UNITY			-0.0117***		
			(0.003)		
COMM_HEALTH				-0.0014	
				(0.003)	
INST_HEALTH					-0.0104***
					(0.004)
Observations	108,535	108,303	108,573	108,664	108,626
R2	0.096	0.096	0.096	0.096	0.096
Controls	Yes	Yes	Yes	Yes	Yes

Notes: for the description of variables see Table 1. The dependent variable is always HITRUN. Results are expressed as marginal effects on the probability to flee after the accident. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. The standard errors reported in parentheses are corrected for heteroskedasticity and clustering of the residuals at the county level. In all models, we control for LOCALSTREET, URBAN, DAYLYLIGHT, CLEARWEATHER, HIGHSPLIM, HOLIDAY, TWOWAY, UNRATE, SHARE_CATH, HOSPITAL, RGDPPC, SHARE_BLACK, DRY, MEX_BORDER (The variables description is reported in Table 1. See Table A4 in Appendix for coefficients and significance level of the control variables). Hour, days of the week, month, and year*state dummies always included but not reported.

TABLE 4b - Estimation results: US Microanalysis (Logit model)

	1	*2*	*3*	*4*	*5*
SOCCAP	-0.0206***				
	(0.004)				
COLL_EFF		-0.0153***			
		(0.003)			
FAMILY_UNITY			-0.0124***		
			(0.003)		
COMM_HEALTH				-0.001	
				(0.004)	
INST_HEALTH					-0.0127***
					(0.004)
Observations	89,515	89,306	89,550	89,635	89,600
R2	0.100	0.100	0.100	0.099	0.100
Controls	Yes	Yes	Yes	Yes	Yes
Victim characteristics	Yes	Yes	Yes	Yes	Yes

Notes: for the description of variables see Table 1. The dependent variable is always HITRUN. Results are expressed as marginal effects on the probability to flee after the accident. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. The standard errors reported in parentheses are corrected for heteroskedasticity and clustering of the residuals at the county level. In all models, we control for LOCALSTREET, URBAN, DAYLYLIGHT, CLEARWEATHER, HIGHSPLIM, HOLIDAY, TWOWAY, UNRATE, SHARE_CATH, HOSPITAL, RGDPPC, SHARE_BLACK, DRY, MEX_BORDER, MALEPED. AGEPED (and its square), WHITEPED (The variables description is reported in Table 1. See Table A5 in Appendix for coefficients and significance level of the control variables). Hour, days of the week, month, and year*state dummies always included but not reported.

TABLE 5 - Falsification test: Local street vs Non-local street (Logit model)

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
	Local Street					**Non-local Street**				
SOCCAP	-0.0272***					-0.0090**				
	(0.004)					*(0.004)*				
COLL_EFF		-0.0235***					-0.0042			
		(0.003)					*(0.004)*			
FAMILY_UNITY			-0.0184***					-0.0051		
			(0.004)					*(0.004)*		
COMM_HEALTH				0.0062					-0.0044	
				(0.005)					*(0.005)*	
INST_HEALTH					-0.0034					-0.0102**
					(0.006)					*(0.004)*
Observations	50,362	50,319	50,379	50,393	50,376	57,147	56,980	57,163	57,236	57,220
R2	0.116	0.116	0.116	0.115	0.115	0.084	0.084	0.084	0.084	0.084
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: for the description of variables see Table 1. The dependent variable is always HITRUN. Results are expressed as marginal effects on the probability to flee after the accident. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. The standard errors reported in parentheses are corrected for heteroskedasticity and clustering of the residuals at the county level. In all models, we control for LOCALSTREET, URBAN, DAYLYLIGHT, CLEARWEATHER, HIGHSPLIM, HOLIDAY, TWOWAY, UNRATE, SHARE_CATH, HOSPITAL, RGDPPC, SHARE_BLACK, DRY, MEX_BORDER (The variables description is reported in Table 1). Hour, days of the week, month, and year*state dummies always included but not reported.

TABLE 6 - Falsification Test: Resident vs Out-of-county drivers (Logit model)

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
	Resident					**Out-of-county**				
SOCCAP	-0.0105***					-0.0024				
	(0.003)					*(0.004)*				
COLL_EFF		-0.0097***					-0.0019			
		(0.002)					*(0.003)*			
FAMILY_UNITY			-0.0087***					-0.0009		
			(0.003)					*(0.003)*		
COMM_HEALTH				0.0049*					-0.0015	
				(0.003)					*(0.003)*	
INST_HEALTH					-0.0009					-0.0001
					(0.004)					*(0.004)*
Observations	68,328	68,287	68,352	68,396	68,372	25,068	25,004	25,073	25,102	25,097
R2	0.076	0.076	0.076	0.075	0.075	0.099	0.100	0.099	0.099	0.099
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: for the description of variables see Table 1. The dependent variable is always HITRUN. Results are expressed as marginal effects on the probability to flee after the accident. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. The standard errors reported in parentheses are corrected for heteroskedasticity and clustering of the residuals at the county level. In all models, we control for LOCALSTREET, URBAN, DAYLYLIGHT, CLEARWEATHER, HIGHSPLIM, HOLIDAY, TWOWAY, UNRATE, SHARE_CATH, HOSPITAL, RGDPPC, SHARE_BLACK, DRY, MEX_BORDER (The variables description is reported in Table 1). Hour, days of the week, month, and year*state dummies always included but not reported.

TABLE 7a - Estimation results using driver's county social capital (Logit model)

	1	*2*	*3*	*4*	*5*
SOCCAP_DR	-0.0063***				
	(0.002)				
COLL_EFF_DR		-0.0055***			
		(0.002)			
FAMILY_UNITY_DR			-0.0053***		
			(0.002)		
COMM_HEALTH_DR				-0.002	
				(0.002)	
INST_HEALTH_DR					-0.0023
					(0.003)
Observations	24,417	24,308	24,429	24,507	24,495
R2	0.100	0.099	0.100	0.099	0.099
Controls	Yes	Yes	Yes	Yes	Yes
Driver Sample	out-of-county	out-of-county	out-of-county	out-of-county	out-of-county

Notes: for the description of variables see Table 1. The dependent variable is always HITRUN. Results are expressed as marginal effects on the probability to flee after the accident. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. The standard errors reported in parentheses are corrected for heteroskedasticity and clustering of the residuals at the county level. In all models, we control for LOCALSTREET, URBAN, DAYLYLIGHT, CLEARWEATHER, HIGHSPLIM, HOLIDAY, TWOWAY, UNRATE, SHARE_CATH, HOSPITAL, RGDPPC, SHARE_BLACK, DRY, MEX_BORDER (The variables description is reported in Table 1). Hour, days of the week, month, and year*state dummies always included but not reported.

TABLE 7b - Estimation results using driver's and accident's county social capital (Logit model)

	1	*2*	*3*	*4*	*5*
SOCCAP	-0.0034				
	(0.004)				
SOCCAP_DR	-0.0065***				
	(0.002)				
COLL_EFF		-0.0033			
		(0.003)			
COLL_EFF_DR		-0.0057***			
		(0.002)			
FAMILY_UNITY			-0.0012		
			(0.003)		
FAMILY_UNITY_DR			-0.0054***		
			(0.002)		
COMM_HEALTH				-0.0012	
				(0.003)	
COMM_HEALTH_DR				-0.002	
				(0.002)	
INST_HEALTH					0.0006
					(0.004)
INST_HEALTH_DR					-0.0023
					(0.003)
Observations	24,386	24,236	24,403	24,507	24,490
R2	0.100	0.100	0.100	0.099	0.098
Equality test (county vs driver social capital)	0.62	0.55	1.31	0.04	0.37
P-Value Chi2	*0.4311*	*0.4587*	*0.2521*	*0.8418*	*0.5413*
Controls	Yes	Yes	Yes	Yes	Yes
Driver Sample	out-of-county	out-of-county	out-of-county	out-of-county	out-of-county

Notes: for the description of variables see Table 1. The dependent variable is always HITRUN. Results are expressed as marginal effects on the probability to flee after the accident. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. The standard errors reported in parentheses are corrected for heteroskedasticity and clustering of the residuals at the county level. In all models, we control for LOCALSTREET, URBAN, DAYLYLIGHT, CLEARWEATHER, HIGHSPLIM, HOLIDAY, TWOWAY, UNRATE, SHARE_CATH, HOSPITAL, RGDPPC, SHARE_BLACK, DRY, MEX_BORDER (The variables description is reported in Table 1). Hour, days of the week, month, and year*state dummies always included but not reported.

TABLE 8 - Estimation results: US Microanalysis (IV Lewbel)

	1	*2*	*3*	*4*	*5*
SOCCAP	-0.0205***				
	(0.004)				
COLL_EFF		-0.0156***			
		(0.004)			
FAMILY_UNITY			-0.0130***		
			(0.004)		
COMM_HEALTH				0.0003	
				(0.004)	
INST_HEALTH					-0.0080*
					(0.005)
Observations	109,273	109,124	109,312	109,404	109,365
R2	0.075	0.075	0.075	0.075	0.075
Hansen J statistic - chi2	131.891	137.081	132.983	130.140	123.287
P-Value	*0.2349*	*0.1507*	*0.2151*	*0.2690*	*0.4251*
Endogeneity test - chi2	0.062	0.029	0.382	0.038	3.004
P-Value	*0.8030*	*0.8649*	*0.5366*	*0.8456*	*0.0831*
Controls	Yes	Yes	Yes	Yes	Yes

Notes: for the description of variables see Table 1. The dependent variable is always HITRUN. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. The standard errors reported in parentheses are corrected for heteroskedasticity and clustering of the residuals at the county level. In all models, we control for LOCALSTREET, URBAN, DAYLYLIGHT, CLEARWEATHER, HIGHSPLIM, HOLIDAY, TWOWAY, UNRATE, SHARE_CATH, HOSPITAL, RGDPPC, SHARE_BLACK, DRY, MEX_BORDER (The variables description is reported in Table 1). Hour, days of the week, month, year and state dummies always included but not reported.

TABLE 9 - Estimation results - Dependent variable: Probability of being identified (Logit model)

	1	*2*	*3*	*4*	*5*
SOCCAP	0.0279***				
	(0.01)				
COLL_EFF		0.0119			
		(0.008)			
FAMILY_UNITY			0.0094		
			(0.009)		
COMM_HEALTH				0.0233**	
				(0.011)	
INST_HEALTH					0.0414***
					(0.012)
Observations	18,781	18,773	18,786	18,794	18,789
R2	0.086	0.085	0.085	0.086	0.086
Controls	Yes	Yes	Yes	Yes	Yes

Notes: for the description of variables see Table 1. The dependent variable is always IDENTIFIED. Results are expressed as marginal effects on the probability of being identified. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. The standard errors reported in parentheses are corrected for heteroskedasticity and clustering of the residuals at the county level. In all models, we control for LOCALSTREET, URBAN, DAYLYLIGHT, CLEARWEATHER, HIGHSPLIM, HOLIDAY, TWOWAY, UNRATE, SHARE_CATH, HOSPITAL, RGDPPC, SHARE_BLACK, DRY, MEX_BORDER (The variables description is reported in Table 1). Hour, days of the week, month, and year*state dummies always included but not reported.

TABLE 10 - Falsification test - Dependent variable: Probability of being identified. Local street vs Non-local street (Logit model)

	1	2	3	4	5	6	7	8	9	10
	Local Street					**Non-local Street**				
SOCCAP	0.0360**					0.0181				
	(0.014)					*(0.013)*				
COLL_EFF		0.0183*					0.0091			
		(0.011)					*(0.01)*			
FAMILY_UNITY			0.0074					0.0037		
			(0.012)					*(0.011)*		
COMM_HEALTH				0.0349**					0.0078	
				(0.014)					*(0.014)*	
INST_HEALTH					0.0455***					0.0331**
					(0.017)					*(0.015)*
Observations	9,918	9,914	9,920	9,921	9,919	8,396	8,392	8,398	8,404	8,402
R2	0.107	0.107	0.107	0.107	0.107	0.092	0.092	0.091	0.091	0.092
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: for the description of variables see Table 1. The dependent variable is always IDENTIFIED. Results are expressed as marginal effects on the probability of being identified. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. The standard errors reported in parentheses are corrected for heteroskedasticity and clustering of the residuals at the county level. In all models, we control for LOCALSTREET, URBAN, DAYLYLIGHT, CLEARWEATHER, HIGHSPLIM, HOLIDAY, TWOWAY, UNRATE, SHARE_CATH, HOSPITAL, RGDPPC, SHARE_BLACK, DRY, MEX_BORDER (The variables description is reported in Table 1). Hour, days of the week, month, and year*state dummies always included but not reported.

TABLE A1 - Correlation matrix: US microanalysis

	HITRUN	SOCCAP	COLL_EFF	FAMILY_UNITY	COMM_HEALTH	INST_HEALTH	LOCALSTREET	URBAN	DAYLYLIGHT	CLEARWEATHER	HIGHSPLIM	HOLIDAY	TWOWAY	UNRATE	SHARE_CATH	HOSPITAL	RGDPPC	SHARE_BLACK	DRY	MEX_BORDER	MALE_PED	AGE_PED	WHITE_PED
HITRUN	1																						
SOCCAP	-0.0873	1																					
COLL_EFF	-0.0855	0.8164	1																				
FAMILY_UNITY	-0.0549	0.7794	0.6483	1																			
COMM_HEALTH	-0.0285	0.3347	-0.0317	-0.0082	1																		
INST_HEALTH	-0.0443	0.5999	0.1637	0.2256	0.3651	1																	
LOCALSTREET	0.0734	-0.0498	-0.0664	0.0301	0.0085	-0.0761	1																
URBAN	0.0245	-0.0341	-0.0698	0.0183	-0.0462	0.0214	0.0697	1															
DAYLYLIGHT	-0.1524	0.0565	0.0217	0.0456	0.0658	0.0396	0.1526	0.0325	1														
CLEARWEATHER	-0.006	-0.0761	-0.0273	-0.0247	-0.0947	-0.0892	0.0345	0.075	0.0862	1													
HIGHSPLIM	-0.0214	0.0502	0.1045	0.0307	0.0252	-0.0647	-0.3737	-0.147	-0.0781	-0.0254	1												
HOLIDAY	0.0182	-0.0045	-0.0003	-0.0064	-0.0081	-0.0009	-0.0118	0.0051	-0.0291	-0.0106	0.0229	1											
TWOWAY	0.0354	0.1033	0.0817	0.0012	0.146	0.0739	0.2925	-0.0639	0.1289	0.001	-0.172	-0.0078	1										
UNRATE	0.0079	-0.2107	-0.1072	-0.2078	-0.0743	-0.1793	0.0744	0.1365	-0.0108	0.011	0.022	0.0064	0.0403	1									
SHARE_CATH	0.0377	0.0658	0.0973	0.1726	-0.1362	-0.0475	0.1115	0.1346	0.0552	0.0171	-0.093	0.008	0.011	0.0543	1								
HOSPITAL	0.0318	-0.2256	-0.346	-0.2022	0.1708	-0.0202	0.0951	0.0585	0.0523	-0.0157	-0.0853	-0.0015	-0.0177	-0.0167	0.1849	1							
RGDPPC	0.0808	-0.1927	-0.27	0.0687	-0.2424	-0.0479	0.2398	0.2362	0.0271	0.0562	-0.221	0.0085	-0.1805	-0.0543	0.4382	0.302	1						
SHARE_BLACK	0.0453	-0.5286	-0.5767	-0.6848	0.0579	0.0297	-0.0445	-0.0047	-0.045	-0.0031	-0.0418	0.0087	-0.0163	0.0643	-0.2174	0.2388	0.0421	1					
DRY	-0.0145	0.0241	0.0553	0.0272	0.0054	-0.0472	-0.0306	-0.0321	0.0048	-0.0027	0.0303	-0.0057	0.0366	0.0024	-0.088	-0.0276	-0.1366	-0.0344	1				
MEX_BORDER	0.0107	-0.0322	0.0576	0.0623	-0.1149	-0.1693	0.0414	0.0291	-0.0077	0.0335	0.0101	0.0026	-0.0437	0.048	0.1541	-0.0539	0.0713	-0.137	-0.0121	1			
MALE_PED	0.0213	-0.0259	-0.0063	-0.0189	-0.0279	-0.0274	-0.0566	-0.0137	-0.0572	0.0073	0.0576	-0.0048	-0.0399	0.0038	-0.0331	-0.0319	-0.0279	0.0105	0.0006	0.0043	1		
AGE_PED	-0.0659	0.0162	0.0046	0.0277	-0.0133	0.02	0.0478	0.0244	0.0987	-0.0205	-0.1421	-0.0226	0.0055	-0.0047	0.083	0.0426	0.0725	-0.0334	-0.0143	0.0111	-0.0348	1	
WHITE_PED	-0.0592	0.1786	0.1962	0.1966	-0.0343	0.0329	-0.0349	-0.0005	0.05	0.0102	0.0275	-0.0024	0.0113	-0.0206	0.0455	-0.1127	-0.0565	-0.3009	0.0179	0.0511	0.012	0.0573	1

Note: for the description of the variables see Table 1.

TABLE A2- Description and summary statistics: US macroanalysis

VARIABLE	DESCRIPTION	Mean	StdD	Min	Max	Obs
PERC_HITRUN	Percentage of fatal pedestrian Hit-and-Run	16.86	3.98	7.13	24.06	51
SOCCAP	Social Capital Index	0	1	-2.15	2.08	51
FAMILY_UNITY	Family Unity Sub-Index (see table A5)	0	1	-3.37	2.62	51
FAM_INTERACTION	Family Interaction Sub-Index (see table A5)	0	1	-2.33	2.59	51
SOCIALSUPPORT	Social Support Sub-Index (see table A5)	0	1	-2.49	2.97	51
COMM_HEALTH	Community Health Sub-Index (see table A5)	0	1	-1.38	3.97	51
INST_HEALTH	Institutional Health Sub-Index (see table A5)	0	1	-3.46	2.18	51
COLL_EFF	Collective Efficacy Sub-Index (see table A5)	0	1	-4.91	1.48	51
PHILANTROPHIC_HEALTH	Philantrophic Health Sub-Index (see table A5)	0	1	-2.23	2.21	51
LRGDPPC	Real GDP per capita (in thousands of dollars)	51,817	19,419	33,101	172,371	51
DENSITY	Population over surface (sq. Miles)	387	1,405	1	10,062	51
UNRATE	Unemployment rate (in percentage)	5.62	1.05	3.20	7.32	51
INSURANCE_COV	Insurance coverage required (see table note)	2.45	1.01	0	4	51
PRISON_SENTENCE	Maximum prison sentence for fleeing after the accident (in year)	9.27	6.61	1.00	30.00	51

Notes: all the variables employed are defined at state level. See Table A5 for a detailed description of the social capital measures. INSURANCE_COV refers to the type of coverage insurance required to carry in each state. It is an ordered variable ranging from 0 to 4. Zero means that in a state there is not vehicle insurance required, while 4 means that in the state are required all the following type of insurance coverage: Bodily Injury, Property Damage Liability, Personal Injury Protection, Uninsured/Underinsured Motorist.

TABLE A3 - Correlation matrix: US Macroanalysis

	PERC_HITRUN	SOCCAP	FAMILY_UNITY	FAM_INTERACTIO	SOCIALSUPPORT	COMM_HEALTH	INST_HEALTH	COLL_EFF	PHILANTROPHIC_	LRGDPPC	DENSITY	UNRATE	INSURANCE_COV	PRISON_SENTENCE
PERC_HITRUN	1													
SOCCAP	-0.4187	1												
FAMILY_UNITY	-0.3412	0.761	1											
FAM_INTERACTION	-0.2646	0.8194	0.4521	1										
SOCIALSUPPORT	-0.4652	0.8943	0.6518	0.7001	1									
COMM_HEALTH	-0.1273	0.6472	0.1693	0.7432	0.583	1								
INST_HEALTH	-0.2413	0.7241	0.4587	0.4741	0.5613	0.3708	1							
COLL_EFF	-0.5264	0.5479	0.6655	0.3203	0.5071	-0.1102	0.3437	1						
PHILANTROPHIC_H	-0.2631	0.8034	0.5935	0.5459	0.619	0.5413	0.5732	0.2621	1					
LRGDPPC	0.3028	0.0024	-0.3056	0.1785	-0.1437	0.5661	0.1013	-0.6367	0.1664	1				
DENSITY	0.2735	-0.1161	-0.4969	0.0898	-0.1845	0.5194	0.0207	-0.6826	0.0437	0.9049	1			
UNRATE	0.362	-0.5821	-0.5981	-0.4067	-0.5509	-0.2731	-0.4012	-0.4475	-0.3728	0.1176	0.2387	1		
INSURANCE_COV	-0.0316	0.0623	0.0124	0.0703	0.0953	0.0505	0.0818	-0.0532	0.038	0.1167	0.1145	0.0468	1	
PRISON_SENTENCE	0.1154	-0.0149	-0.1015	0.0263	-0.0831	-0.113	0.1782	0.0343	-0.0041	-0.2073	-0.1586	0.1168	-0.0072	1

Note: for the description of the variables see Table A2.

TABLE A4 - Estimation results: US Microanalysis (Logit model)

	1	2	3	4	5
SOCCAP	-0.0189***				
	(0.003)				
COLL_EFF		-0.0142***			
		(0.003)			
FAMILY_UNITY			-0.0117***		
			(0.003)		
COMM_HEALTH				-0.0014	
				(0.003)	
INST_HEALTH					-0.0104***
					(0.004)
LOCALSTREET	0.0606***	0.0609***	0.0614***	0.0615***	0.0612***
	(0.004)	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*
URBAN	0.0095***	0.0100***	0.0096***	0.0096***	0.0097***
	(0.003)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
DAYLYLIGHT	-0.0579***	-0.0582***	-0.0579***	-0.0582***	-0.0582***
	(0.007)	*(0.007)*	*(0.007)*	*(0.007)*	*(0.007)*
CLEARWEATHER	-0.0090***	-0.0087**	-0.0089***	-0.0089***	-0.0092***
	(0.003)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
HIGHSPLIM	-0.0081	-0.0084*	-0.0085	-0.0092*	-0.0093*
	(0.005)	*(0.005)*	*(0.005)*	*(0.005)*	*(0.005)*
HOLIDAY	0.0372***	0.0374***	0.0370***	0.0369***	0.0369***
	(0.008)	*(0.008)*	*(0.008)*	*(0.008)*	*(0.008)*
TWOWAY	0.0444***	0.0447***	0.0441***	0.0444***	0.0443***
	(0.003)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
UNRATE	0.0029**	0.0050***	0.0044***	0.0066***	0.0053***
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*
SHARE_CATH	0.0544**	0.0668***	0.0462**	0.0515**	0.0506**
	(0.022)	*(0.022)*	*(0.023)*	*(0.021)*	*(0.022)*
HOSPITAL	-0.0375	-0.0404	-0.0353	-0.0115	-0.0231
	(0.026)	*(0.029)*	*(0.037)*	*(0.038)*	*(0.035)*
(LN)RGDPPC	0.0105***	0.0095***	0.0122***	0.0114***	0.0122***
	(0.001)	*(0.002)*	*(0.002)*	*(0.002)*	*(0.001)*
SHARE_BLACK	0.0844***	0.1009***	0.1056***	0.1647***	0.1571***
	(0.025)	*(0.025)*	*(0.026)*	*(0.021)*	*(0.02)*
DRY	-0.0064	-0.0064	-0.0066	-0.0091	-0.0128
	(0.02)	*(0.021)*	*(0.02)*	*(0.02)*	*(0.02)*
MEX_BORDER	0.0093	0.0096	0.0109	0.0097	0.0088
	(0.013)	*(0.013)*	*(0.013)*	*(0.013)*	*(0.013)*
Observations	108,535	108,303	108,573	108,664	108,626
R2	0.096	0.096	0.096	0.096	0.096

Notes: for the description of variables see Table 1. The dependent variable is always HITRUN. Results are expressed as marginal effects on the probability to flee after the accident. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. The standard errors reported in parentheses are corrected for heteroskedasticity and clustering of the residuals at the county level. Hour, days of the week, month, and year*state dummies always included but not reported.

TABLE A5 - Estimation results: US Microanalysis (Logit model)

	1	2	3	4	5
SOCCAP	-0.0206***				
	(0.004)				
COLL_EFF		-0.0153***			
		(0.003)			
FAMILY_UNITY			-0.0124***		
			(0.003)		
COMM_HEALTH				-0.001	
				(0.004)	
INST_HEALTH					-0.0127***
					(0.004)
LOCALSTREET	0.0631***	0.0632***	0.0636***	0.0638***	0.0637***
	(0.004)	*(0.004)*	*(0.005)*	*(0.005)*	*(0.005)*
URBAN	0.0081**	0.0085**	0.0081**	0.0083**	0.0085**
	(0.004)	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*
DAYLYLIGHT	-0.0531***	-0.0536***	-0.0531***	-0.0536***	-0.0534***
	(0.007)	*(0.007)*	*(0.007)*	*(0.007)*	*(0.007)*
CLEARWEATHER	-0.0101***	-0.0098***	-0.0100***	-0.0100***	-0.0103***
	(0.004)	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*
HIGHSPLIM	-0.0065	-0.0069	-0.0070	-0.0076	-0.0076
	(0.006)	*(0.006)*	*(0.006)*	*(0.006)*	*(0.006)*
HOLIDAY	0.0398***	0.0399***	0.0395***	0.0394***	0.0396***
	(0.009)	*(0.009)*	*(0.009)*	*(0.009)*	*(0.009)*
TWOWAY	0.0463***	0.0466***	0.0460***	0.0464***	0.0462***
	(0.003)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
UNRATE	0.0027*	0.0048***	0.0043***	0.0067***	0.0052***
	(0.002)	*(0.001)*	*(0.002)*	*(0.002)*	*(0.002)*
SHARE_CATH	0.0594**	0.0746***	0.0508**	0.0569**	0.0540**
	(0.024)	*(0.024)*	*(0.025)*	*(0.024)*	*(0.024)*
HOSPITAL	-0.016	-0.0177	0.0092	0.0428	0.0239
	(0.071)	*(0.072)*	*(0.083)*	*(0.083)*	*(0.082)*
(LN)RGDPPC	0.0103***	0.0093***	0.0120***	0.0112***	0.0121***
	(0.002)	*(0.002)*	*(0.002)*	*(0.002)*	*(0.002)*
SHARE_BLACK	0.0444*	0.0603**	0.0654**	0.1273***	0.1192***
	(0.026)	*(0.026)*	*(0.028)*	*(0.024)*	*(0.023)*
DRY	-0.0039	-0.0048	-0.0048	-0.0074	-0.0119
	(0.022)	*(0.022)*	*(0.022)*	*(0.022)*	*(0.022)*
MEX_BORDER	0.0064	0.0064	0.0080	0.007	0.0061
	(0.014)	*(0.014)*	*(0.014)*	*(0.014)*	*(0.013)*
MALEPED	0.0029	0.003	0.003	0.0032	0.0031
	(0.003)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
AGEPED	0.0025***	0.0025***	0.0025***	0.0026***	0.0026***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
AGEPED2	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
WHITEPED	-0.0290***	-0.0291***	-0.0290***	-0.0290***	-0.0291***
	(0.004)	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*
Observations	89,515	89,306	89,550	89,635	89,600
R2	0.100	0.100	0.100	0.099	0.100

Notes: for the description of variables see Table 1. The dependent variable is always HITRUN. Results are expressed as marginal effects on the probability to flee after the accident. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. The standard errors reported in parentheses are corrected for heteroskedasticity and clustering of the residuals at the county level. Hour, days of the week, month, and year*state dummies always included but not reported.

TABLE A6 - Estimation results: US Microanalysis (Logit model)

	1	2	3	4	5
SOCCAP	-0.0210***				
	(0.004)				
COLL_EFF		-0.0160***			
		(0.003)			
FAMILY_UNITY			-0.0125***		
			(0.003)		
COMM_HEALTH				-0.0009	
				(0.004)	
INST_HEALTH					-0.0121***
					(0.004)
Observations	89,515	89,306	89,550	89,635	89,600
R2	0.097	0.096	0.096	0.096	0.096
Controls	Yes	Yes	Yes	Yes	Yes

Notes: for the description of variables see Table 1. The dependent variable is always HITRUN. Results are expressed as marginal effects on the probability to flee after the accident. Superscripts ***, ** and * denote statistical significance at the 1, 5 and 10 percent level, respectively. The standard errors reported in parentheses are corrected for heteroskedasticity and clustering of the residuals at the county level. In all models, we control for LOCALSTREET, URBAN, DAYLYLIGHT, CLEARWEATHER, HIGHSPLIM, HOLIDAY, TWOWAY, UNRATE, SHARE_CATH, HOSPITAL, RGDPPC, SHARE_BLACK, DRY, MEX_BORDER (The variables description is reported in Table 1). Hour, days of the week, month, and year*state dummies always included but not reported.

TABLE A7 - County-Level Social Capital Index Indicators

Indicators	Data Source	Notes
Family Unity Subindex		
Share of births in past year to women who were unmarried	American Community Survey, 2012-2016, 5-year estimates	American FactFinder Table S1301
Share of women ages 35-44 who are currently married (and not separated)	American Community Survey, 2012-2016, 5-year estimates	American FactFinder Table B12002
Share of own children living in a single-parent family	American Community Survey, 2012-2016, 5-year estimates	American FactFinder Table B09002
Community Health Subindex		
Registered non-religious non-profits per 1,000	IRS, Business Master File, 12/2015; ACS population estimates, 7/2015 (2015 vintage)	via National Center for Charitable Statistics & American FactFinder Table PEPANNRES
Religious congregations per 1,000	U.S. Religion Census: Religious Congregations and Membership Study, 2010	via Association of Religious Data Archives, census conducted 2009-11
Informal Civil Society Sub-Index	See notes	combination of share who volunteered, who attended a public meeting, who report having worked with neighbors to fix/improve something, who served on a committee or as an officer, who attended a meeting where politics was discussed, and who took part in a demonstration in the past year (see text for details)
Institutional Health Subindex		
Average (over 2012 and 2016) of votes in the presidential election per citizen age 18+	Election Administration and Voting Survey; ACS, 2012-2016, 5-year estimates	U.S. Election Assistance Commission; EAVS voting combined with American FactFinder Table B05003 estimates of citizens 18+; votes unavailable for Alaska counties, which we assign the state-wide voting rate
Mail-back response rates for 2010 census	Census Bureau	via University of Michigan Population Studies Center, Institute for Social Research
Confidence in Institutions Sub-Index	Volunteer Supplement to the November 2013 Current Population Survey	combination of share reporting at least some confidence in corporations, in the media, and in public schools (see text for details)
Collective Efficacy		
Violent crimes per 100,000	FBI, Uniform Crime Reporting Statistics, 2008-14	via County Health Rankings, various editions: 2017 (2012-14 UCR data), 2015 (2010-12), 2014 (2009-11), and 2013 (2008-10)

Source: The Geography of Social Capital in America.

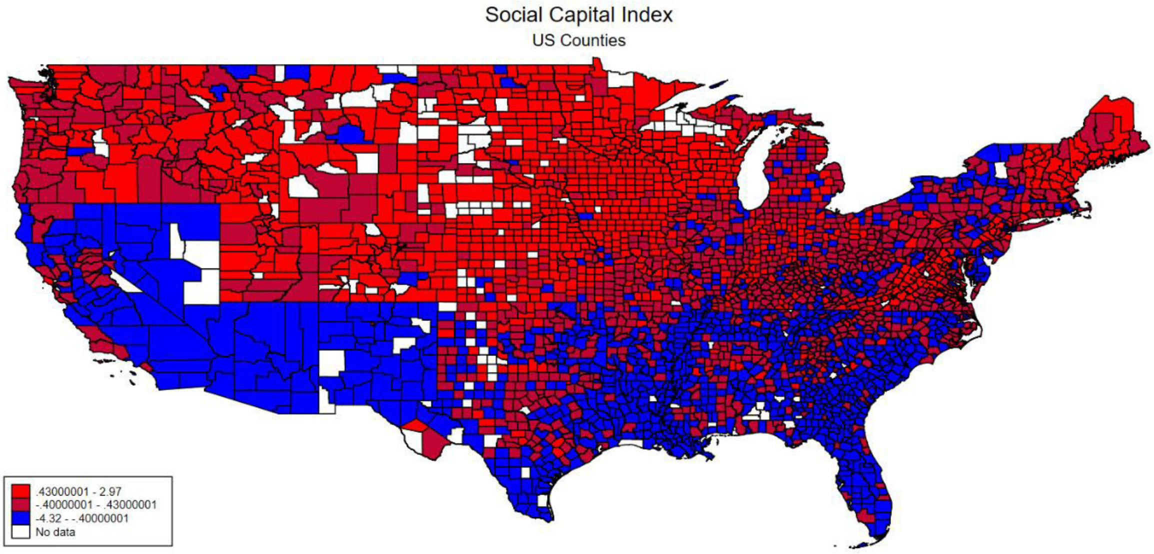
TABLE A8 - State-Level Social Capital Index Indicators

Indicators	Data Source	Notes
Family Unity Subindex		
Share of births in past year to women who were unmarried	American Community Survey, 2012-2016, 5-year estimates; 2007-2011, 5-year estimates for 27 counties in eight states	American FactFinder Table S1301
Share of women ages 35-44 who are currently married (and not separated)	American Community Survey, 2012-2016, 5-year estimates	American FactFinder Table B12002
Share of own children living in a single-parent family	American Community Survey, 2012-2016, 5-year estimates	American FactFinder Table B09002
Family Interaction SubIndex		
Share who report child spends at least 4 hours per weekday in front of a TV	National Survey of Children's Health, 2016	includes watching TV, videos, or video games
Share who report child spends at least 4 hours per weekday on electronic device, excluding homework	National Survey of Children's Health, 2016	includes computers, cell phones, handheld video games, and other electronic devices
Share who report someone in the family read to child every day in past week	National Survey of Children's Health, 2016	restricted to parents with child 0-5 years old
Social Support Subindex		
Share saying they get the emotional support they need only sometimes, rarely, or never	Behavioral Risk Factor Surveillance System	analysis of BFRSS microdata, 2006 & 2010 estimates averaged to get pre- and post-recession estimates
Average number of close friends reported by adults	Civic Engagement Supplement to the November 2008 Current Population Survey	
Share of adults reporting they and their neighbors do favors for each other at least 1x/month	Volunteer Supplement to the November 2013 Current Population Survey	
Share of adults reporting they can trust all or most of their neighbors	Volunteer Supplement to the November 2013 Current Population Survey	
Community Health Subindex		
Share of adults who report having volunteered for a group in the past year	Volunteer Supplement to the September 2015 Current Population Survey	
Share who report having attended a public meeting re. community affairs in past year	Volunteer Supplement to the September 2015 Current Population Survey	
Share who report having worked with neighbors to fix/improve something in past year	Volunteer Supplement to the September 2015 Current Population Survey	
Share of adults who served on a committee or as an officer of a group	Volunteer Supplement to the November 2013 Current Population Survey	
Share who attended a meeting where political issues were discussed in past year	Civic Engagement Supplement to the November 2008 Current Population Survey	
Share who took part in march/rally/protest/demonstration in past year	Civic Engagement Supplement to the November 2008 Current Population Survey	

Membership organizations per 1,000	County Business Patterns, 2015; ACS population estimates, 7/2015 (2015 vintage)	American FactFinder Tables CB1500A11 & PEPANNRES
Registered non-religious non-profits plus religious congregations per 1,000	IRS, Business Master File, 12/2015; ACS population estimates, 7/2015 (2015 vintage); U.S. Religion Census: Religious Congregations and Membership Study, 2010	IRS data via National Center for Charitable Statistics & American FactFinder Table PEPANNRES; congregation data obtained via Association of Religious Data Archives, census conducted 2009-11
Institutional Health Subindex		
Average (over 2012 and 2016) of votes in the presidential election per citizen age 18+	Election Administration and Voting Survey	U.S. Election Assistance Commission; EAVS voting combined with American FactFinder Table B05003 estimates of citizens 18+; votes unavailable for Alaska counties, which we assign the statewide voting rate
Mail-back response rates for 2010 census	Census Bureau	
Share of adults reporting some or great confidence in corporations to do what is right	Volunteer Supplement to the November 2013 Current Population Survey	
Share of adults reporting some or great confidence in the media to do what is right	Volunteer Supplement to the November 2013 Current Population Survey	
Share of adults reporting some or great confidence in public schools to do what is right	Volunteer Supplement to the November 2013 Current Population Survey	
Collective Efficacy		
Violent crimes per 100,000	FBI, Uniform Crime Reporting Statistics, 2008-14	
Philanthropic Health		
Share who report having made a donation of >$25 to a charitable group in past year	Volunteer Supplement to the September 2015 Current Population Survey	

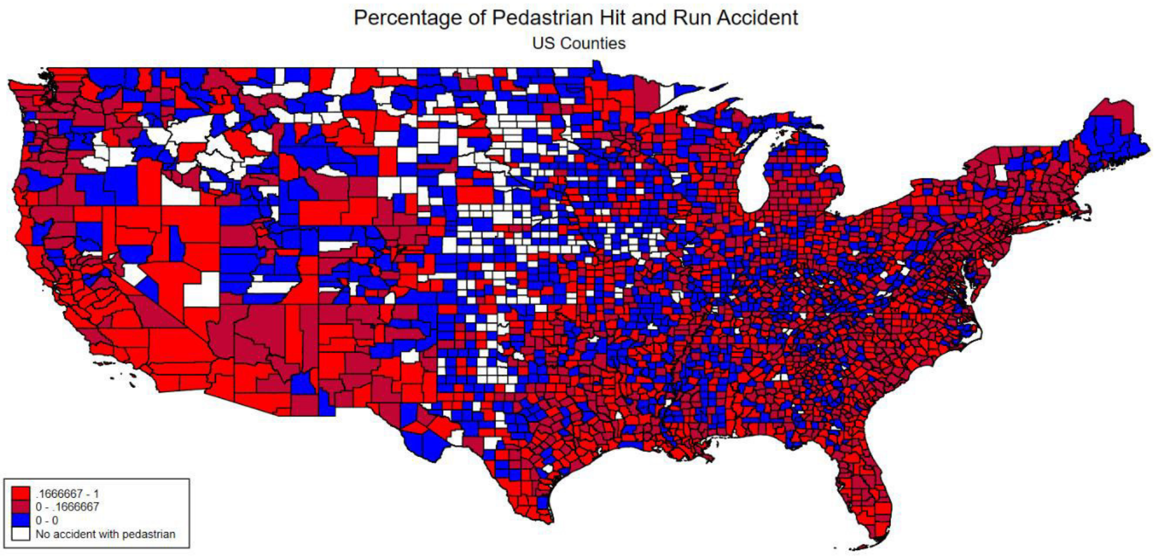
Source: The Geography of Social Capital in America.

Figure 1. Social Capital Index Scores in the US, by county



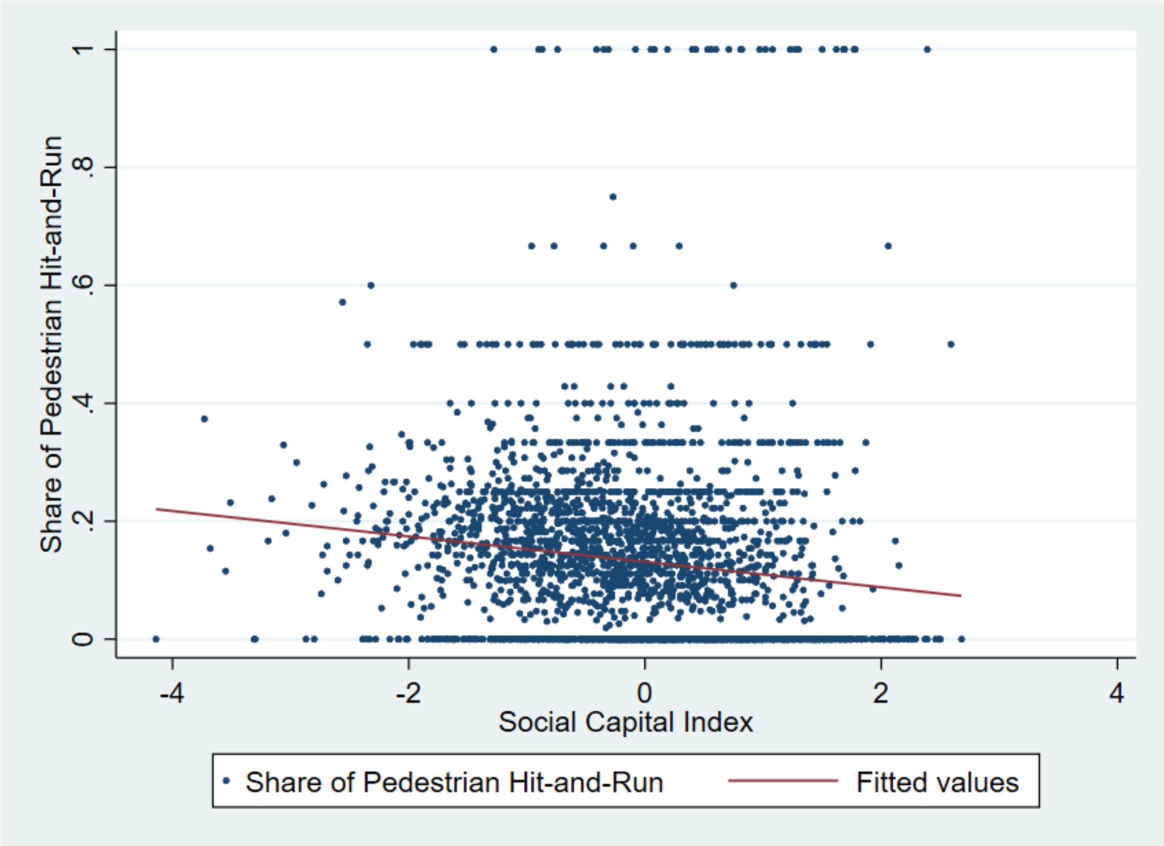
Authors' elaboration on The Geography of Social Capital project data

Figure 2. Percentage of a pedestrian hit-and-run accident in the US, by county



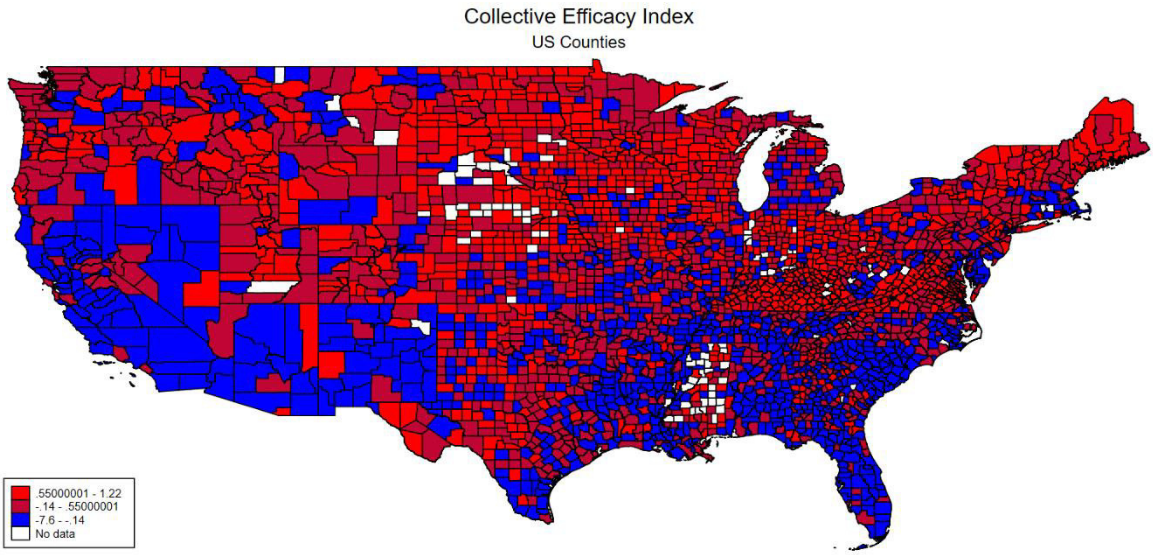
Authors' elaboration on FARS data

Figure 3. Share of pedestrian hit-and-run (2000 – 2018) and Social Capital Index, by county



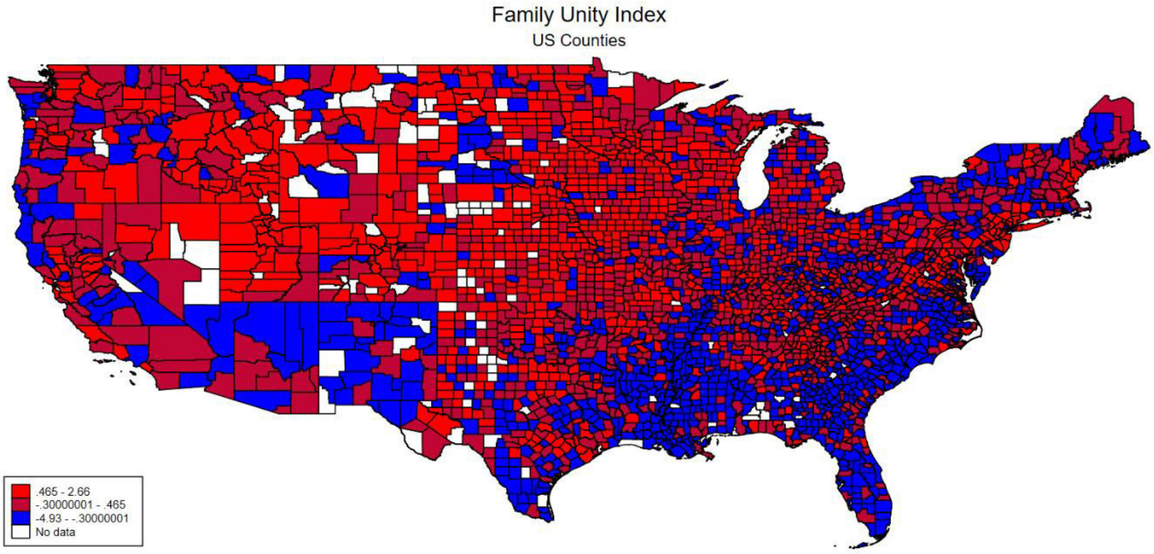
Authors’ elaboration on The Geography of Social Capital project data and FARS data.

Figure A3. Collective Efficacy Index Scores in US, by county



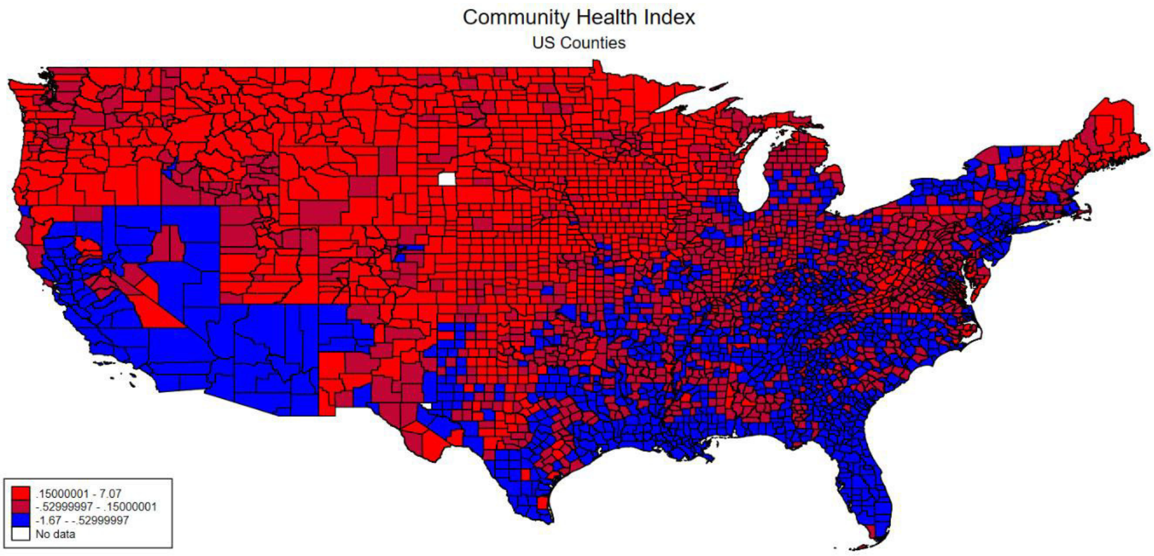
Authors’ elaboration on The Geography of Social Capital project data

Figure A2. Family Unity Index Scores in US, by county



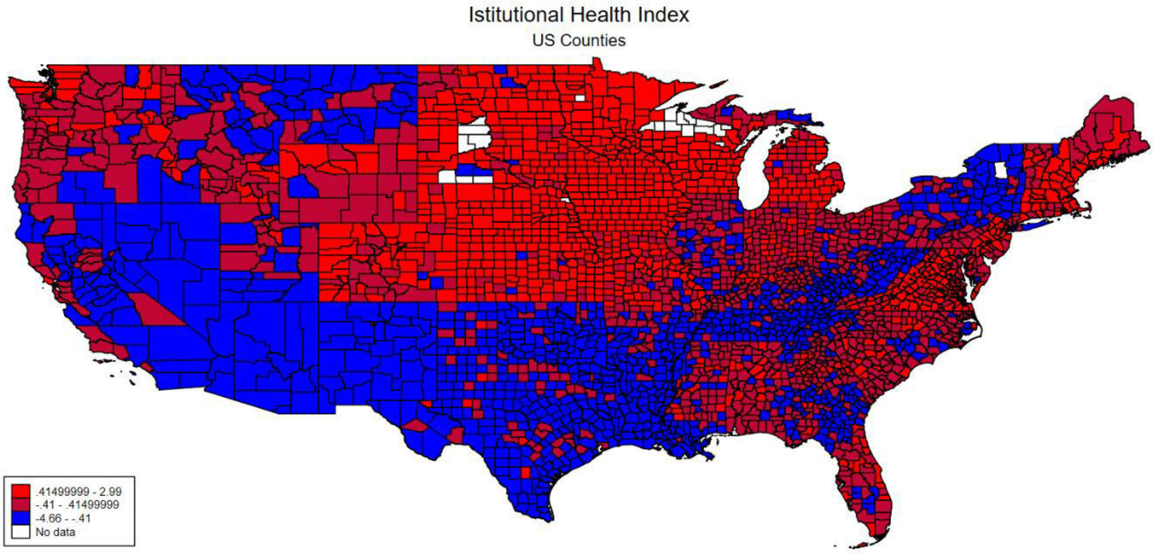
Authors' elaboration on The Geography of Social Capital project data

Figure A3. Community Health Index Scores in US, by county



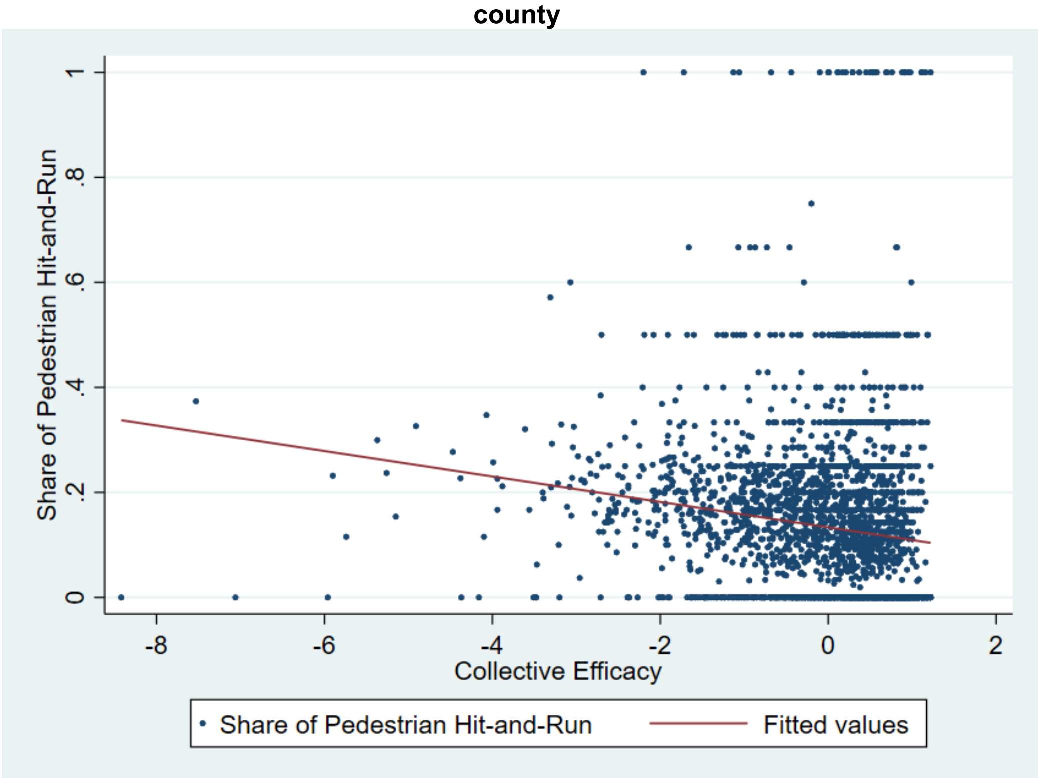
Authors' elaboration on The Geography of Social Capital project data

Figure A4. Institutional Health Index Scores in US, by county



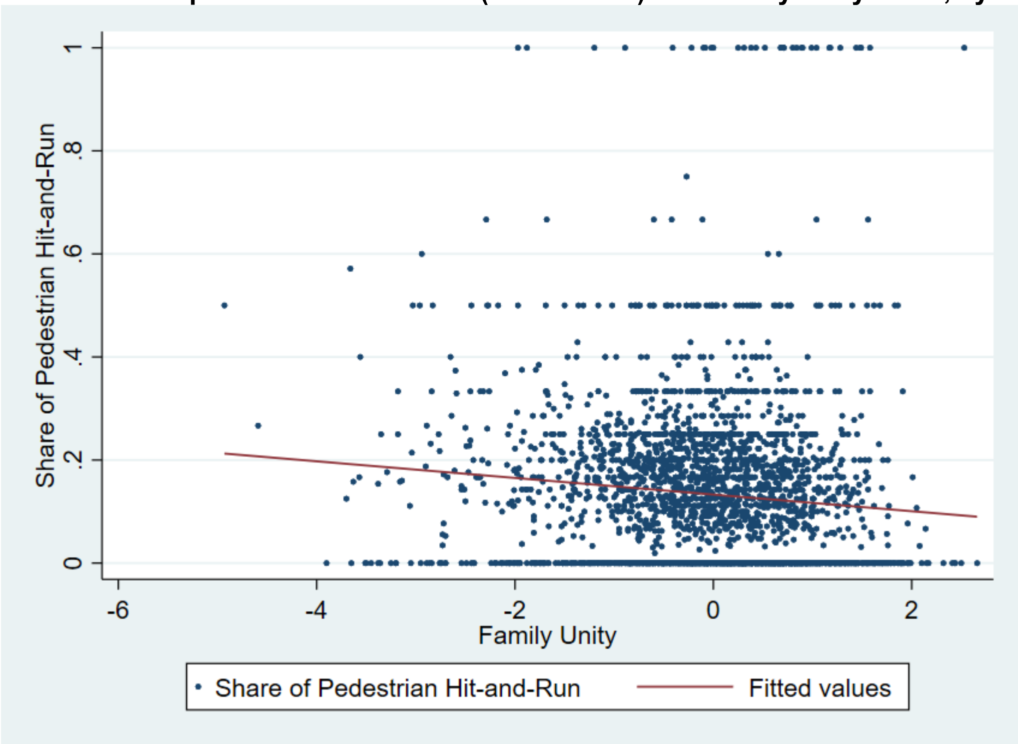
Authors' elaboration on The Geography of Social Capital project data

Figure A5. Share of pedestrian hit-and-run (2000 – 2018) and Collective Efficacy Index, by county



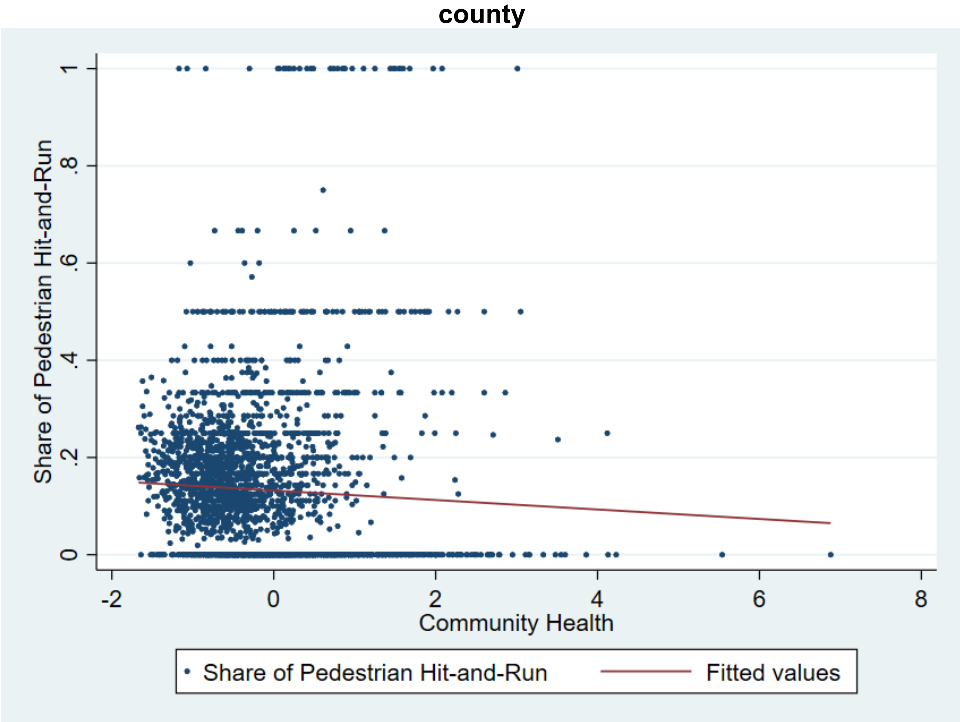
Authors' elaboration on The Geography of Social Capital project data and FARS data.

Figure A6. Share of pedestrian hit-and-run (2000 – 2018) and Family Unity Index, by county



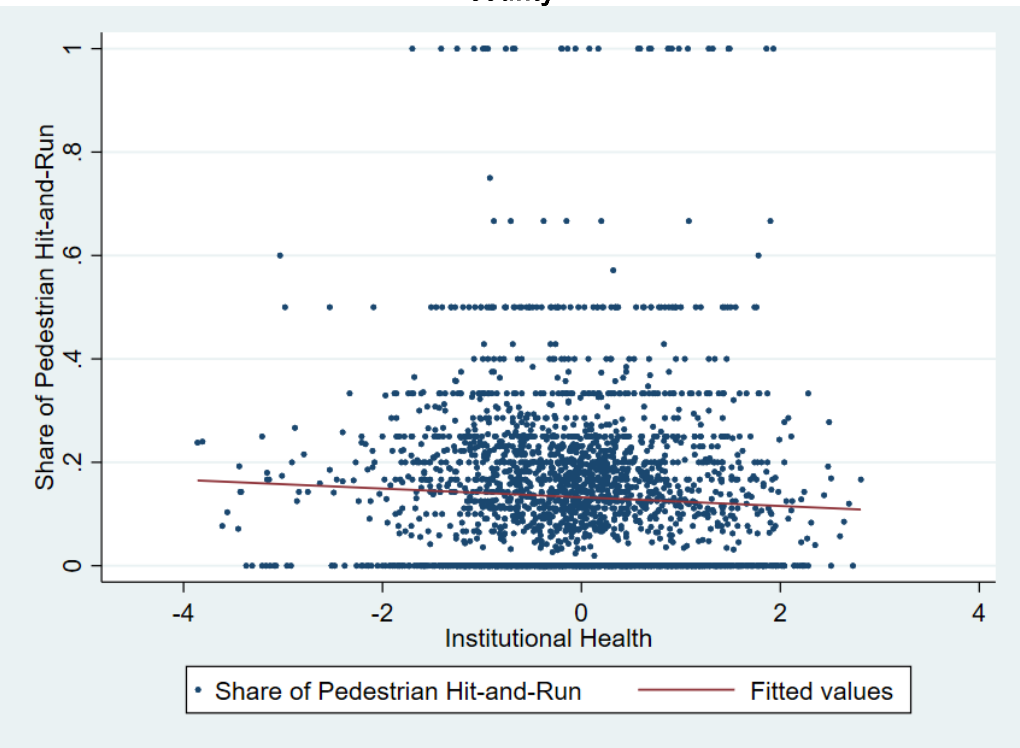
Authors' elaboration on The Geography of Social Capital project data and FARS data.

Figure A7. Share of pedestrian hit-and-run (2000 – 2018) and Community Health Index, by county



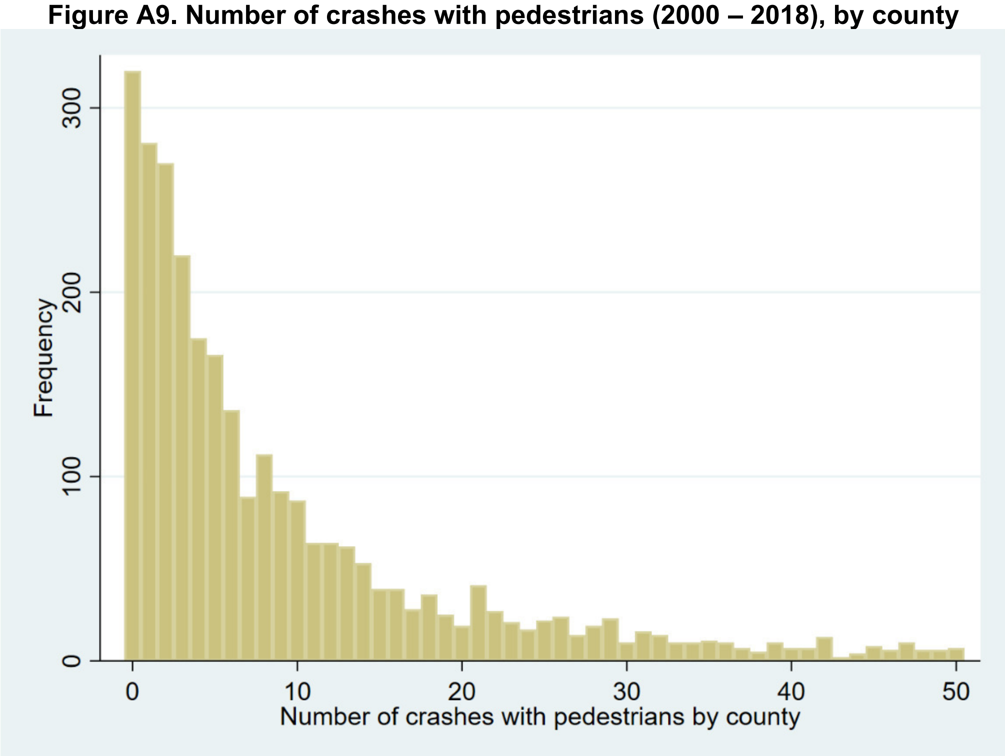
Authors' elaboration on The Geography of Social Capital project data and FARS data.

Figure A8. Share of pedestrian hit-and-run (2000 – 2018) and Institutional Health Index, by county



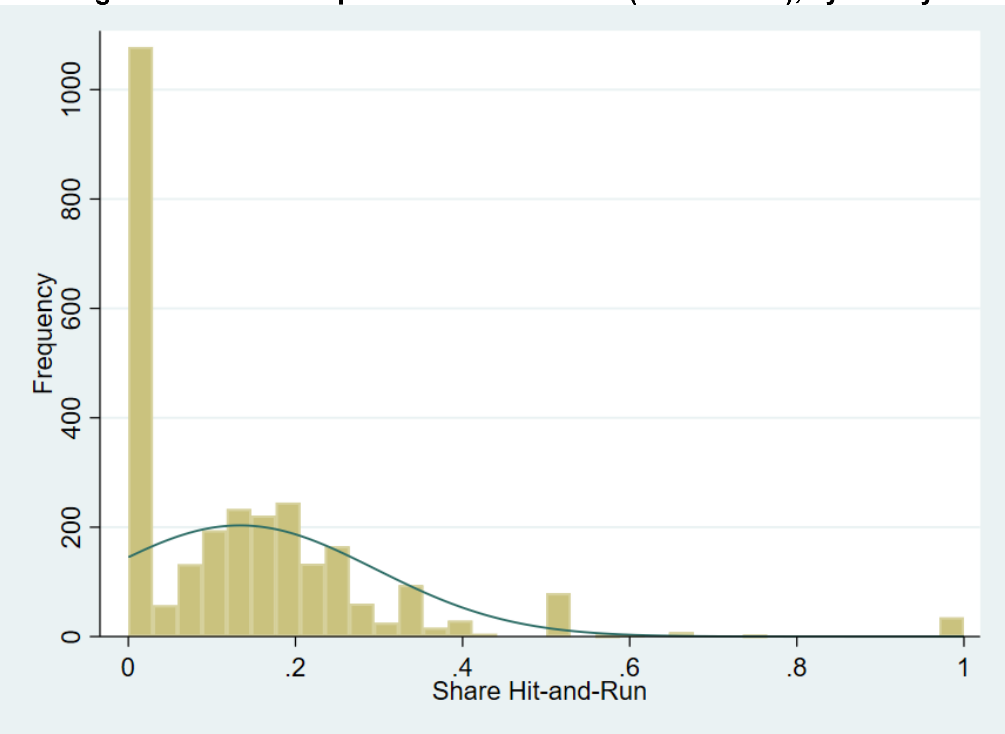
Authors' elaboration on The Geography of Social Capital project data and FARS data.

Figure A9. Number of crashes with pedestrians (2000 – 2018), by county



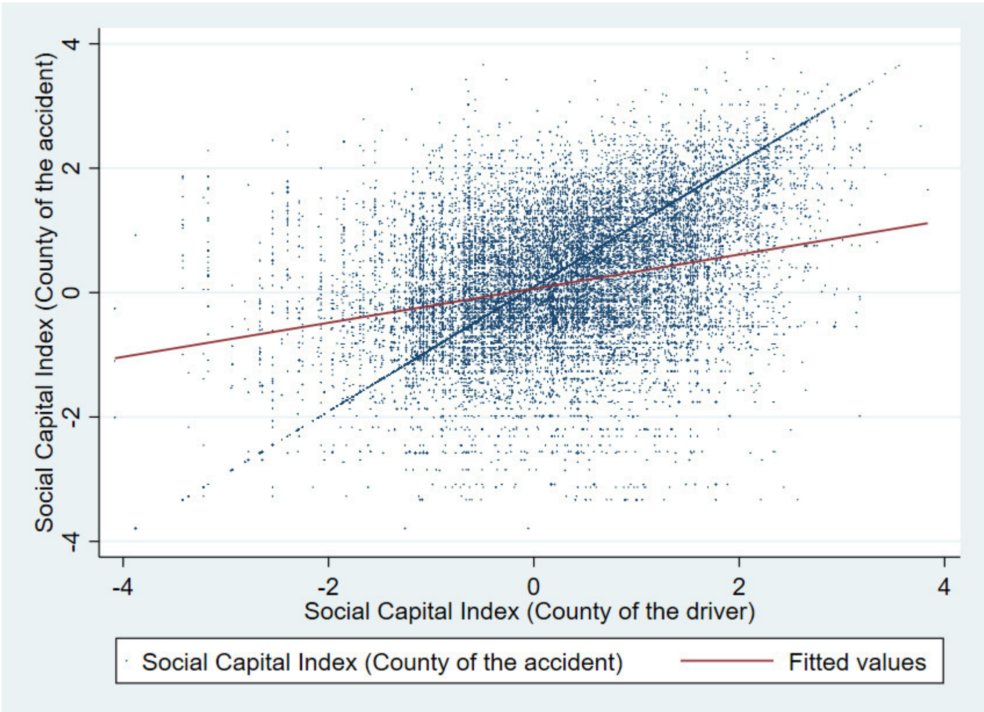
Authors' elaboration on FARS data. To have a readable figure, we have truncated the distribution at 50 crashes.

Figure A10. Share of pedestrian hit-and-run (2000 – 2018), by county



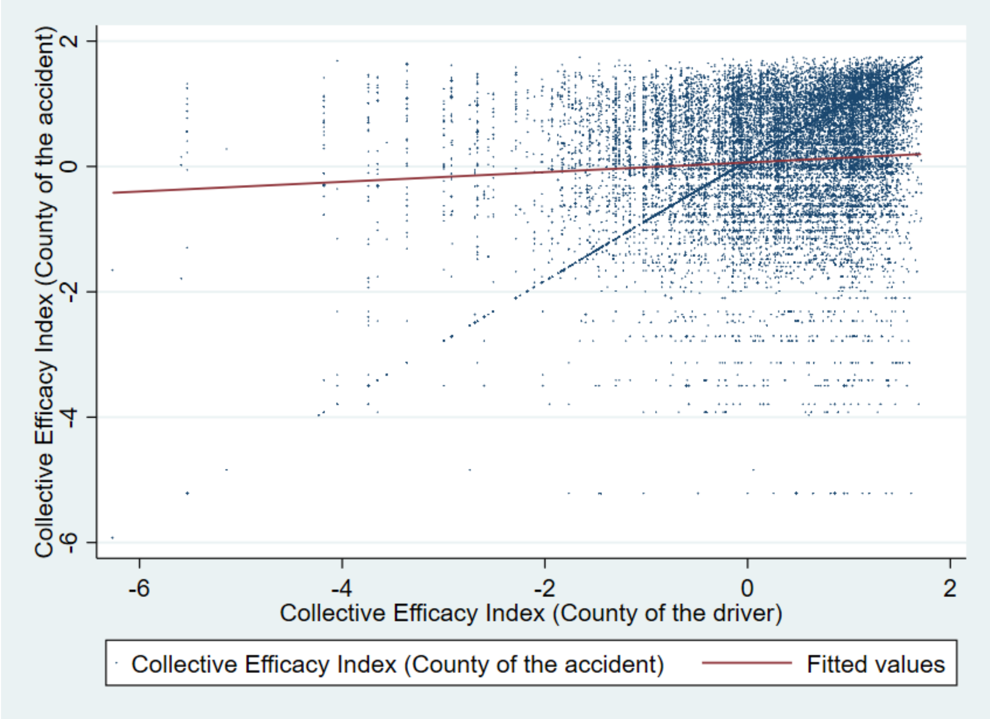
Authors' elaboration on FARS data.

Figure A11. Social Capital Index county of the accident and Social Capital Index county of the driver



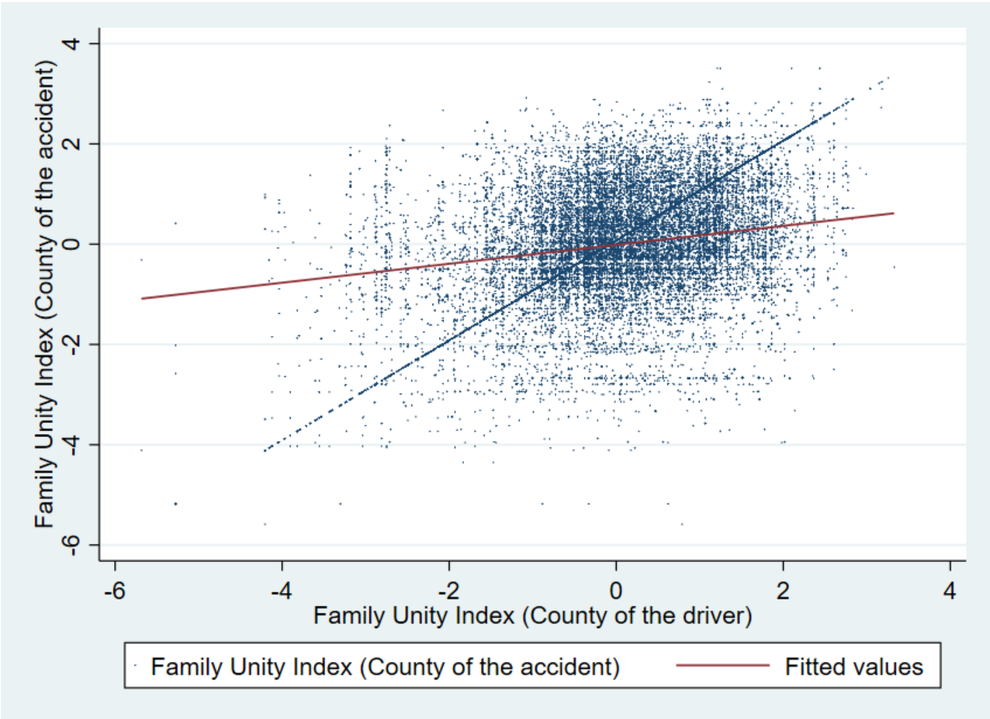
Authors' elaboration on The Geography of Social Capital project data and FARS data.

Figure A12. Collective Efficacy Index county of the accident and Collective Efficacy Index county of the driver



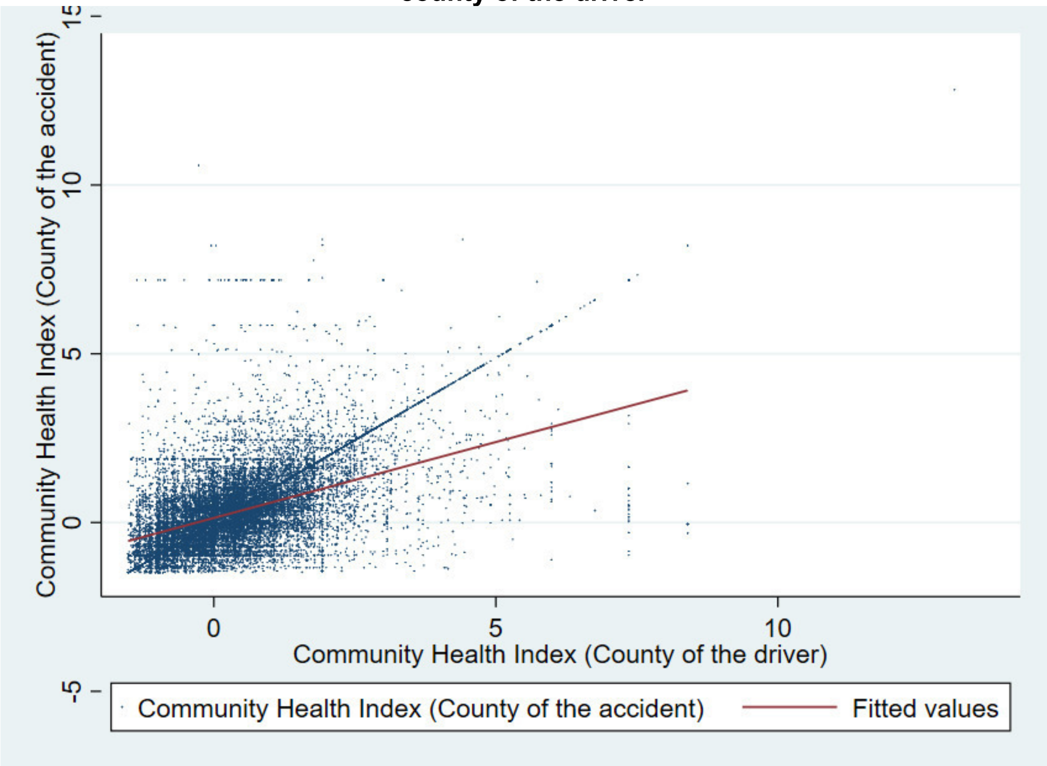
Authors' elaboration on The Geography of Social Capital project data and FARS data.

Figure A13. Family Unity Index county of the accident and Family Unity Index county of the driver



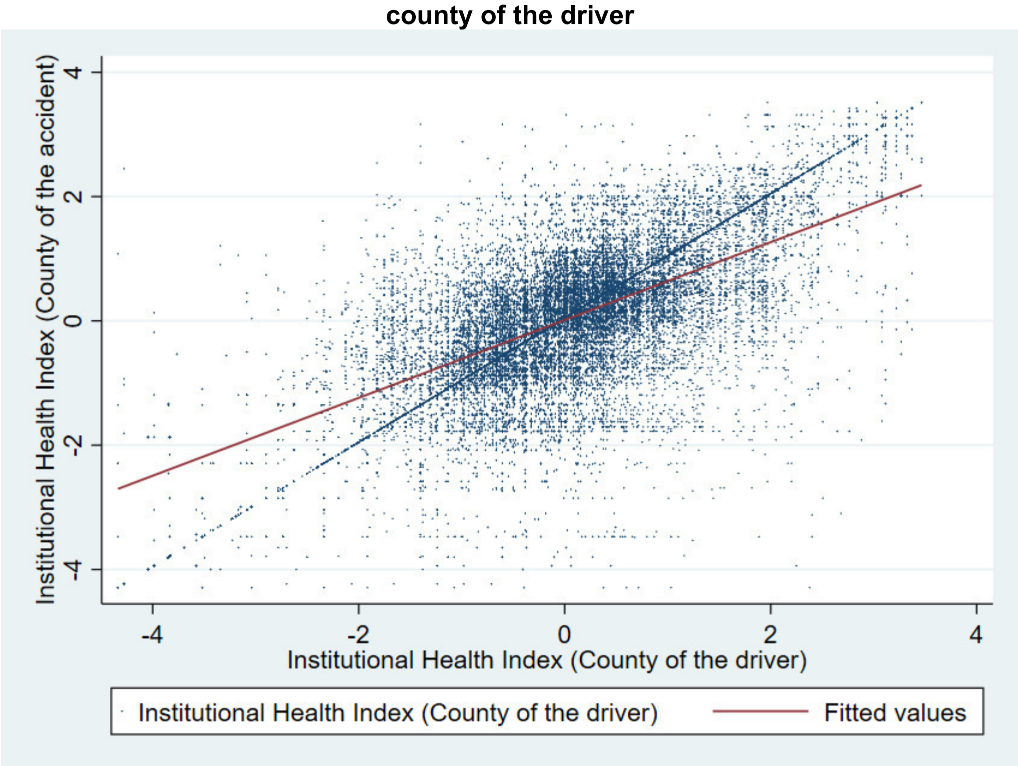
Authors' elaboration on The Geography of Social Capital project data and FARS data.

Figure A14. Community Health Index county of the accident and Community Health Index county of the driver



Authors' elaboration on The Geography of Social Capital project data and FARS data.

Figure A15. Institutional Health Index county of the accident and Institutional Health Index county of the driver



Authors' elaboration on The Geography of Social Capital project data and FARS data.