Measures of Speeding from a GPS-based Travel Behavior Survey

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Abstract

Objective:

Lacking information about actual driving speed on most roads in the Minneapolis - St. Paul region, we determine car speeds using observations from a GPS-based travel survey. Speed of travel determines the likelihood of, and consequences of, collisions. We identify the road segments where speeding occurs. This paper then analyzes the relationship between road network structure, traveler characteristics, and speeding using GPS data collected from 152 individuals over a 7 day period as part of the Minneapolis - St. Paul Travel Behavior Inventory.

Methods:

To investigate the relationship, we employed an algorithm and process to match the GPS data with GIS databases accurately (1). Comparing actual travel speed from GPS data with posted speed limits, we measure where and when speeding occurs, and by whom. We posit that road network structure and demographics shape the decision to speed.

Results:

Speeding is widespread in both high speed limit zones (e.g. 60 mph (97 km/h)) and low speed limit zones (less than 25 mph (40 km/h)); in contrast, speeding is less common in the 30 - 35 mph (48-56 km/h) zones. The results suggest driving patterns depend on the road type. We also find that when there are many intersections on the road, the average link speed (and speeding) drops. Long links are conducive to speeding. Younger drivers, and more educated drivers also speed more, and speeding is higher in the evening.

Conclusions:

Road design and network structure affects the likelihood of speeding. Use of increasingly available GPS data allows more systematic empirical analysis of designs and topologies that are conducive to road safety.

Keywords

GPS, speeding, speed limit, network structure, road geometry, travel behavior

Introduction

Speed of travel determines the likelihood of, and consequences of, collisions. Yet little is known about the extent and magnitude of the speeding problem on most roads due to a lack of systematic data. Speeding behavior, driving faster than the speed limit, is affected by the road environment, the vehicle, and the driver (2; 3). Although other researchers (4; 5; 6; 7) have analyzed reasons for speeding regarding drivers, traffic condition, and vehicles, we posit that the road network structure also has an effect on speeding.

Our paper corroborates results showing more speeding at the upper and lower levels of speed limit ranges (7), which suggests that drivers change their speed limit compliance patterns depending on the road type, and that speed limits which are not consistent with driver expectations of appropriate speed are more likely to be disregarded. When there are many intersections on the road network, the average speed on the road linking those intersections would reduce because of traffic signals, traffic conditions, and approaching vehicles from other directions.

In order to analyze the relationship between network structure variables and speeding, we need to collect enormous amount of traffic data over a broad area. Historically, traffic detectors and area studies have been used to analyze the traffic data. However, the amount of data on local roads from such studies are small and infrequent. Therefore, in our paper we take advantage of GPS data, which contain time and position (latitude, longitude, altitude), and allows us to compute travel distance speed. While this set of data comes from a 2010-11 travel survey, as GPS data become more widespread with the diffusion of smartphones and other devices, we anticipate this kind of analysis will become increasingly common.

In this paper, we analyze the relationship between demographics, road network structure, and the degree of speeding from a GPS dataset. To investigate the spatial relationships, we employ an algorithm and process to accurately match the GPS data and GIS maps. We then regress GPS speed observations with speed limits, link length, and demographic data.

Methods

Hypotheses

We posit that speeding is affected by environmental and personal characteristics. We enumerate specific hypotheses below:

1. H1: Link length – Long link length (long spacing between intersections) is correlated with speeding,(8) as there are fewer conflicts and less requirements for deceleration.
2. H2: Hierarchy (Road type) – Position near the top of the hierarchy of roads (e.g. freeways and limited access facilities) is correlated with speeding (9). Compared with local roads, the driver is less affected by external factors on freeways. This is operationalized by looking at speed limit category. We note there are locations that curve, gradient, and other factors may also affect speed limits, though this is not particulaly common in the Minneapolis - St. Paul region. Other measures of hierachy, such as formal classification might also be used.
3. H3: Age – Younger drivers speed more regularly (10).
4. H4: Gender – Male drivers speed more regularly (11).
5. H5: Education Level – Better educated drivers will speed more. Education is generally correlated with income, which often shows this effect (12).
6. H6: Time of Day – Speeding occurs most often in periods unaffected by traffic congestion and when enforcement is lower. This would be the evening and overnight periods (13).

Degree of Speeding

We calculate speeding behavior from two perspectives:

- Whether speeding occurs or not (*Percentage of speeding*) – When the driving speed is over the speed limit, the value becomes 1. If not, the value becomes 0.
- How much the driver exceeds the speed limit (*Degree of speeding*) – The result of percentage of speeding is critical because "driving at 60 mph in 40 mph speed limit zone" and "driving at 41 mph in 40 mph speed limit zone" are identical outcomes. Therefore, we also analyze another speeding behavior by calculating how much each GPS datapoint exceeds the speed limit. *Degree Of Speeding* is defined in Equation 1.

$$\text{Degree Of Speeding} = \frac{\text{Driving Speed}}{\text{Speed Limit}} \tag{1}$$

  When the value is 1, driving speed equals the speed limit, and when the value is more than 1, the data show speeding.

Data

This research uses GPS data from the 2010 Twin Cities (Minneapolis - St. Paul area) Travel Behavior Inventory (TBI2010) administered by the Metropolitan Council between 2010 and 2012 (most data were collected in 2011) that has been used in a variety of studies (14; 15; 16; 17; 18; 19; 20; 21). The TBI is a large, roughly decennial, travel survey of a 1% sample of households in the Twin Cities region. The survey collects data on household and individual socio-economic and demographics, and collects travel diary information (start and end time, purpose, mode, accompaniment, vehicle) about each trip made by each member of the household on a single day. To supplement the data, and prepare for future data collections, a small sample of the TBI was also equipped with a GPS device (22). Each subject in the GPS component of the TBI carried a GPS pendant for 7 days. The raw GPS data contain the following trip information: Speed (km/h), Longitude, Latitude, Altitude (meters), Date (year/month/day), Time (hour/minute/second), Distance (meters), Course (degree), Number of satellites, and Horizontal Dilution of Precision (HDOP). Seven consecutive days of movement with one second recording interval for each person were collected.

Since the initial GPS data doesn't record each trip and the time that the GPS data is disconnected, we define the trip based on the time difference. We divide the initial GPS data into trips when a time difference between GPS data locations exceeds 300 seconds.

However, the GPS data alone do not contain personal information (e.g. gender, age). Therefore, we complement the GPS data with the associated records from the TBI2010 Household Interview Survey (e.g., Household data, Personal information, Trip data). These data can be matched on Person ID. Among 274 GPS subjects (drawn from 250 households), 152 travelers have IDs matching the survey and no other missing data, satisfying conditions that both ends of the trips are within the study region, speeds were greater than 5 km/h, the traveler is over 16, and mode was automobile, allowing us to analyze those participants. We append the GPS data with personal information describing each subject's gender, age, and education. The other travelers were excluded from further analysis.

With the purpose of understanding actual speed limit data, we use a GIS database maintained by the Metropolitan Council and The Lawrence Group (TLG) that covers the majority of road segments in the Twin Cities seven county metropolitan area. The database contains 290,231 links, and each link has several attributes (e.g. speed limit, length of link, street name, one-way).

To conduct the analysis, we use QGIS (version 2) (23), an open source geographic information system. The GPS data are matched to the GIS database using the procedure outlined in (1).

While the advantages of GPS data are clear (large diverse sample of links over a broad area with varying conditions and many drivers), it has disadvantages. GPS does not present a complete census of drivers on a particular link over a given study period the way more traditional point-based speeding measurements might. So there is the possibility of bias emerging, especially if the sample favors those who voluntarily use GPS, who might be more male, young, high income, and technologically inclined (and perhaps more likely to speed as a result). As GPS samples become larger, this issue is likely to be mitigated.

The remaining 2,560 trips (from 152 individuals) are compiled to analyze in the statistical package *R* 3.0.

We analyze the results from integrated GPS points. GPS points were recorded every second; however, it is considered that speeding patterns of drivers in the same link are similar from second-to-second. Therefore, we integrate multiple GPS points for each link for each driver for each trip into a single analysis record; we separate the link data depending for each driver and for each trip because driving environments and driving patterns are different based on other trip conditions and for different drivers. The total number of GPS points is 115,536 (152 drivers on 24,262 links).

Moreover, in order to eliminate the fixed effect prior to estimation, we use a dummy variable regression. We introduce a dummy variable for each individual along with the independent variables.

Results

Descriptive Analysis

For 2,560 trips, comprising 1,172,103 GPS points, we regress the relationship between road network variables, demographics, and speeding. As Table 1 illustrates, most of the data are concentrated on 30, 35, 40 and 55 mph speed limit zone. Moreover, relatively few points are in low speed limit zones (less than 20 mph) and high speed limit zones (70 mph). (Note some travel that is retained in the analysis is on private roads or in parking lots, which explains travel on roads with 5 mph speed limits).

The bar chart shows the percentage of speeding on each speed limit zone (Figure 1). Overall, 23.3% of GPS observations exceed the speed limit. It can also be seen that speeding behavior is significant in low speed limit zones (e.g. from 5 to 25 mph) and high speed limit zones (e.g. from 55 to 65 mph). The number of individuals (N = *) suggests that most participants encountered speed limits between 25 and 65 mph while driving.

The 20 mph speed limit zone stand at 88.8%, and it is followed by 5 and 25 mph speed limit zone at 80.9%, 73.3% respectively. However, the amount of data in low speed limit zones are relatively small, therefore more data are required in order to improve the reliability of this result. In addition to low speed limit zones, speeding in high speed limit zones (from 45 to 70 mph) is also more than average. Speed limits from 30 to 40 mph have less speeding than lower and higher speed limit zones, the 30 mph speed limit zone is the lowest with only 10.1% speeding.

Figure 2 illustrates how much drivers exceed the speed limit. From 5 mph to 30 mph, the value of median falls as the speed limit rises. In contrast, from 30 mph to 70 mph the median slightly rises as the speed limit increases. This result suggests that many drivers exceed the speed limit significantly in low speed limit zones; on the other hand, they tend to drive nearer the speed limit in high speed limit zones. For intermediate speed limit zones, they are likely to drive below the speed limit.

We analyze speeding by time-of-day in Figure 3. Overall, speeding behavior varies by time of day and the percentage of speeding at night exceeds that during the day, with a peak at 4am of 64.7%, and it is followed by 5am and 11pm (hour 23) at 40.1% and 39.8% respectively. On the other hand, 8am and 9am are smaller than other morning hours, it appears that this result is related to the effect of rush hour. It is assumed that drivers cannot drive faster because of traffic conditions. Although the percentage of speeding at 3am is considerably lower than other time zones (3.7%), the number of participants are very small (N=3) and it appears that this result might be significantly influenced by individual factors.

Figure 4 illustrates the relationship between link length and speeding behavior. Y axis is *Degree of Speeding* defined in Equation 1. Figure 4 shows that when link lengths are longer, drivers are more likely to exceed the speed limit.

Clearly driving styles vary individually, some drivers are chronic speeders (even while knowingly being monitored by a GPS unit, though it was clearly not aimed at speed enforcement), while others consistently travel below the speed limit, and almost never except the speed limit as shown in Figure 5. However only a handful of subjects avoided speeding for the entire 7-day period.

Statistical Results

Next, we analyze the relationship between several variables (road network structure and personal information) and speeding using an OLS regression with individual fixed effects. Table 2 shows the list of dependent variable and independent variables. Table 3 shows the results of the regression analysis. We don't report individual driver statistical estimates here, but these estimates can be found in (1), and their distribution is shown in Figure 6.

While the t-value of *speed_40*, *speed_45*, *speed_50*, *age_55_to_64*, *age_85_and_over* and *male* are small, the t-value of other variables are large. Overall F-test shows that F value is 280.5 and p-value is less than 2.2e-16. Therefore, this model shows high significance. Overall the R^2 is 0.29.

A positive coefficient value indicates that when the street length is long, speeding is likely to occur, corroborating theory and the descriptive statistics.

Degree of speeding varies by speed limit. It occurs most at 25 mph, and also on links with a 55, 60, and 65 mph limit. However, 30 and 35 mph speed limit zones are negatively associated with speeding.

Persons who are young, drive overnight (24:00 to 6:00), and/or are educated speed more, corroborating our hypotheses. The age category with the most speeding is 25-34. In contrast with earlier results, we find no evidence of more speeding by males, the variable is statistically insignificant.

A correlation test finds the independent variables here are not meaningfully correlated. The demographic variables are independent of each other and roadway type and speed limit.

Discussion

This paper investigates GPS-based speed data from 152 subjects to examine the relationship between road network structure and speeding. The most pertinent findings from the results are that speeding behavior is significant in both low and high speed limit zones, and long link length is correlated with speeding.

Multivariate regression analysis finds persons who are older, drive in the afternoon, and/or are less educated speed less than younger age groups, other times of the day, and/or more educated drivers.

Other studies mention that elderly, female and uneducated drivers who don't often drive on interurban roads are likely to follow the speed limit (4; 7). We did not see differentiation by gender, in contrast with our own previous work and others (24). To corroborate our findings, we need to see this result replicated in further studies.

Speeding behavior across speed limit zones has been previously analyzed (7), and according to both that result and our result, speeding illustrates a 'V-shape' across all speed limit zones. In a previous study, the 60 mph speed limit zone had the lowest speeding behavior (7) while our result shows the 30 mph speed limit zone is the lowest. We posit that the difference in road characteristics might affect the result.

We investigate GPS data of each participants for 7 days; however, 51.0% of GPS data were removed in our map-matching algorithm in order to ensure no false positives. Future research will aim to reduce the amount of excluded data (false negatives) using more accurate map-matching methods (25).

Future research should also increase the sample size with observations from more GPS units. We expect this will become easier over time as GPS units and the associated data become ubiquitous.

Future analysis should address other measures of roadway geometry and network structure, which are now more readily obtained through standardized scripts (26). Two specific hypotheses would relate to discontinuity of speed limit zones – we anticipate that a large discontinuity would be correlated with speeding – and curvature – we expect straight roads are correlated with speeding.

The results might be useful to decision-makers, engineers, and planners. Speeding problems are widespread in many areas, and speeding increases crash risk. Being able to identify the types of roads that lead to speeding should help road designers rethink their designs in a way that would mitigate the issue.

It might be useful to infer that since long links are associated with speeding, new street designs should have shorter lengths, and links should be shortened with breaks like intersections or traffic calming measures. While, as these data are cross-sectional rather than longitudinal, they cannot confirm that such changes would reduce speeding, the results are supportive. These findings could be corroborated if followed up by carefully designed studies showing the before and after effects. New urbanist street designs, including denser street networks (the antithesis of long lengths) have been shown to reduce crashes for instance, posited to be due to lowered speeds (27).

Adjusting speed limits may also reduce speeding, but may or may not increase safety depending on the direction of adjustment. Lowered speed limits on non-limited access roads along with improved designs to encourage lower speeds and better, including automated, enforcement, or even in-vehicle speed-limiters, may help in this regard (28).

A higher speeding rate among young adults is found again in this study, which may be ameliorated with better enforcement and education, and more restrictive licensure (29).

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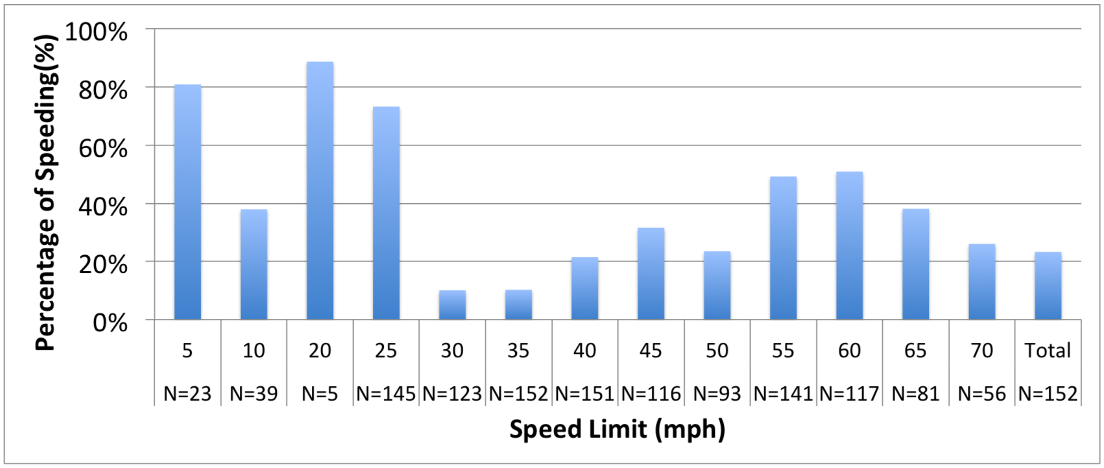
Figures and Tables



(N = *) indicates number of individuals persons encountering that particular speed limit

Figure 1: Percentage of speeding across speed limit zones

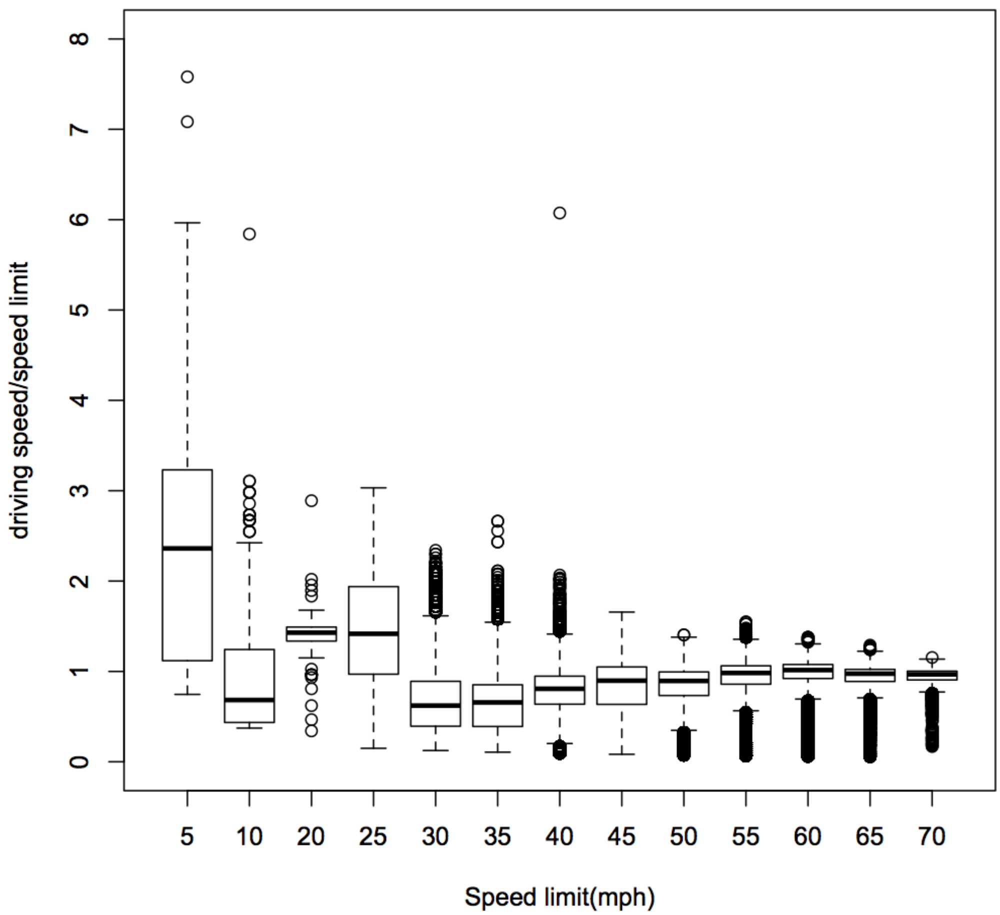


Figure 2: Degree of speeding across speed limit zones

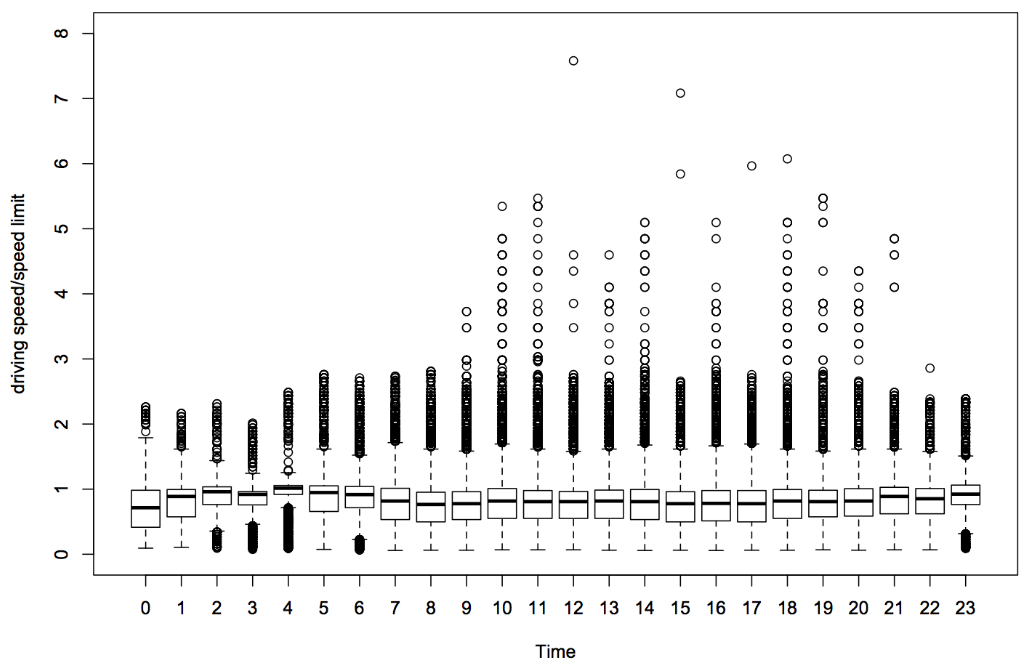
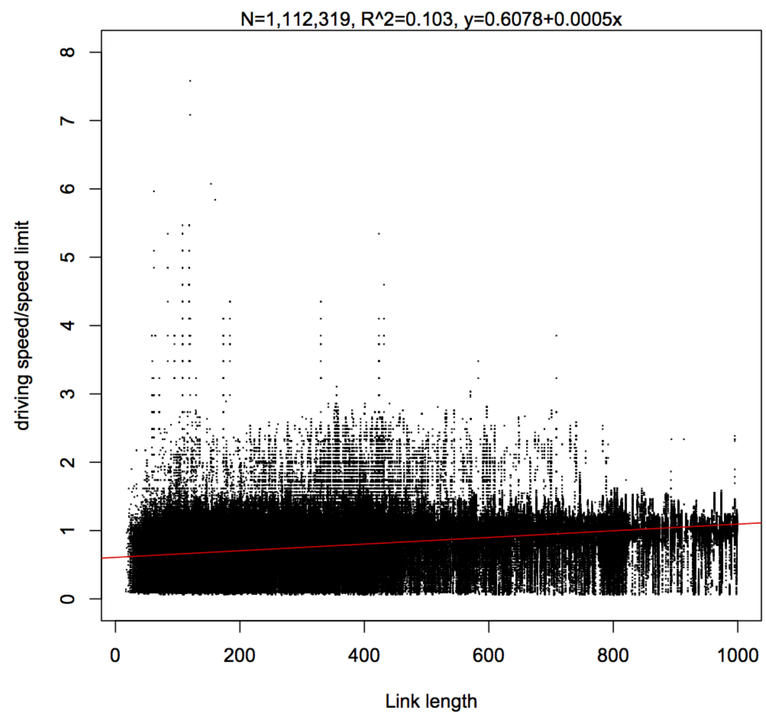


Figure 3: Degree of speeding by time of day



(link length is less than 1,000m)

Figure 4: Relationship between link length and speeding

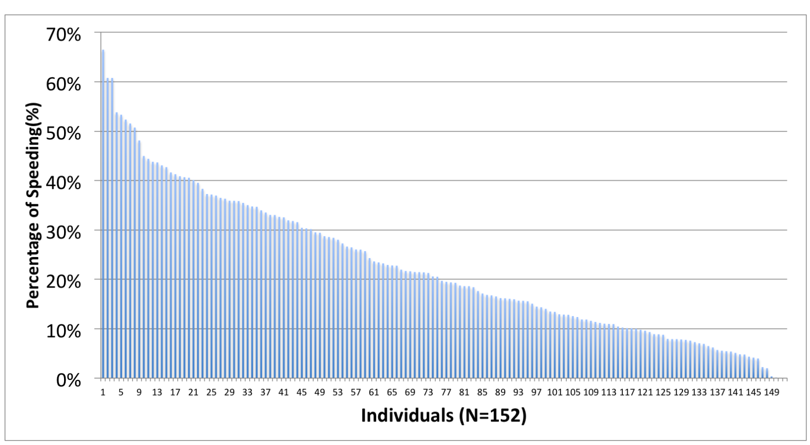


Figure 5: Percentage of speeding per individual

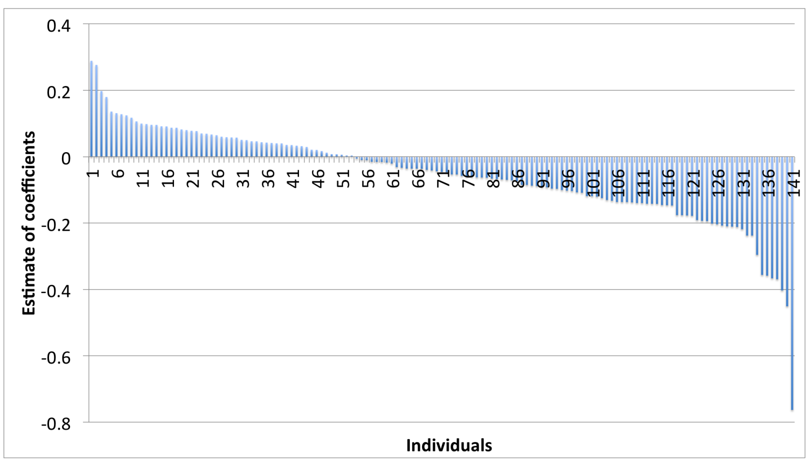


Figure 6: Estimate of coefficients per individuals

Table 1: Total data in each speed limit zone

	GPS data		GIS link	
Speed limit (mph)	**# of pts.**	**%**	**# of links**	**%**
5	759	0.1%	181	0.1%
10	2,364	0.2%	354	0.1%
20	80	0.0%	227	0.1%
25	20,867	1.8%	4,245	1.5%
30	133,339	11.4%	24,204	8.3%
35	377,960	32.2%	223,198	76.9%
40	346,876	29.6%	29,209	10.1%
45	22,624	1.9%	1,921	0.7%
50	20,001	1.7%	939	0.3%
55	118,160	10.1%	3,523	1.2%
60	91,164	7.8%	836	0.3%
65	28,416	2.4%	768	0.3%
70	9,493	0.8%	214	0.1%
Total	1,172,103	100.0%	290,231	100.0%

Table 2: List of dependent and independent variables

Dependent variable

Variables	Definition
Speeding	Speed data / speed limit zone

Independent variables

Variables	Definition
Street length	Link length
speed_25	Indicator, 1= speed limit zone is less than 25 mph, 0 = otherwise
speed_30	Indicator, 1= speed limit is 30 mph, 0 = otherwise
speed_35	Indicator, 1= speed limit is 35 mph, 0 = otherwise
speed_40	Indicator, 1= speed limit is 40 mph, 0 = otherwise
speed_45	Indicator, 1= speed limit is 45 mph, 0 = otherwise
speed_50	Indicator, 1= speed limit is 50 mph, 0 = otherwise
speed_55	Indicator, 1= speed limit is 55 mph, 0 = otherwise
speed_60	Indicator, 1= speed limit is 60 mph, 0 = otherwise
speed_65	Indicator, 1= speed limit is 65 mph, 0 = otherwise
speed_70	Indicator, 1= speed limit is 70 mph, 0 = otherwise*
age_18_to_24	Indicator, 1= age is 18 to 24, 0 = otherwise*
age_25_to_34	Indicator, 1= age is 25 to 34, 0 = otherwise
age_35_to_44	Indicator, 1= age is 35 to 44, 0 = otherwise
age_45_to_54	Indicator, 1= age is 45 to 54, 0 = otherwise
age_55_to_64	Indicator, 1= age is 55 to 64, 0 = otherwise
age_65_to_74	Indicator, 1= age is 65 to 74, 0 = otherwise
age_75_to_84	Indicator, 1= age is 75 to 84, 0 = otherwise
age_85_and_over	Indicator, 1= age is more than 85, 0 = otherwise
male	Indicator, 1= gender is male, 0 = female
education_0	Indicator, 1= education level is High school graduate and Vocational/Technical training, 0 =otherwise*
education_1	Indicator, 1= education level is Some college or Associates degree, 0 = otherwise
education_2	Indicator, 1= education level is Bachelors degree or Graduate/Post-graduate degree, 0 = otherwise
morning	Indicator, 1= time is 06:00 to 12:00, 0 = otherwise
afternoon	Indicator, 1= time is 12:00 to 18:00, 0 = otherwise
evening	Indicator, 1= time is 18:00 to 24:00, 0 = otherwise
overnight	Indicator, 1= time is 24:00 to 06:00, 0 = otherwise*

Note: * indicates variable excluded from regression to avoid Dummy Variable Trap.

Table 3: Degree of Speeding. Fixed Effects Model

Ind. Var.	Estimate	t-value	
(Intercept)	8.386e-01	35.082	***
streetlength	1.280e-04	34.736	***
speed_25	6.587e-01	53.206	***
speed_30	-3.703e-02	-3.125	**
speed_35	-1.177e-01	-10.162	***
speed_40	-8.413e-03	-0.727	
speed_45	-3.285e-03	-0.255	
speed_50	8.432e-03	0.636	
speed_55	1.056e-01	9.164	***
speed_60	9.919e-02	8.538	***
speed_65	3.506e-02	2.823	**
age_25_to_34	7.488e-02	4.963	***
age_35_to_44	-1.055e-01	-3.933	***
age_45_to_54	-2.184e-01	-8.490	***
age_55_to_64	-3.575e-02	-1.513	
age_65_to_74	-1.572e-01	-7.345	***
age_75_to_84	-5.696e-02	-3.927	***
age_85_and_over	-3.847e-02	-1.474	
male	-1.026e-02	-0.580	
education_1	1.520e-01	9.020	***
education_2	1.347e-01	4.676	***
morning	-3.225e-02	-4.726	***
afternoon	-3.566e-02	-5.254	***
evening	-2.295e-02	-3.285	**

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signif. Codes: 0 '***' 0.001,'**',0.01 '*' 0.05 '.' 0.1 ' ' 1

Multiple R-squared	0.2851
F-statistic	280.5
p-value	<0.000

Note: Individual fixed effects not reported in table. Distribution shown in Figure 6.