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Trajectories of Kinematic Risky Driving Among Novice Teenagers

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Abstract

Objectives—Elevated gravitational force event rates are associated with the likelihood of a crash or near crash and provide an objective measure of risky driving. The purpose of this research is to examine the patterns over time of kinematic measures of risky driving among novice teenage drivers.

Methods—Driving data were collected from 42 newly-licensed teenage drivers during the first 18 months of licensure. Data recording systems installed in participants' vehicles provided information on driving performance and driver characteristics. Latent class and logistic regression models were used to analyze trajectories of elevated gravitational-force (g-force) event rates, called kinematic risky driving, with respect to risk groups and associated factors.

Results—Kinematic risky driving over the 18-month study period was best characterized as two classes, a higher-risk and a lower-risk class. The rate of kinematic risky driving during the first 6 months generally maintained over 18 months. Indeed, of those classified by latent class analysis as higher risk, 88.9%, 94.4% and 94.4% had average event rates above the median in the 1st, 2nd, and 3rd 6-month periods, respectively, indicating substantial tracking over time. Friends' risky driving, friends' risky behavior, self-reported risky driving, and perceptions about risky driving and driving privileges were associated with trip-level rates of kinematic risky driving. However, none of these factors was associated with trip-level rates after stratifying by overall risk in a latent class model, although friend's risky driving was marginally significant.

Conclusion—Kinematic risky driving tended to track over time within the lower and higher risky driving groups. Self-reported risky driving and having risky friends were predictors of kinematic risky driving rates, but these variables did not explain the heterogeneity within higher and lower classes of risky drivers.

Keywords

adolescence; risk taking; motor vehicle crashes; naturalistic driving

1. INTRODUCTION

Teenage drivers have high crash rates (National Highway Traffic Safety Administration, 2009). Research based on self-reported (McCartt et al., 2003), police-reported (Twisk and Stacey, 2007; Williams, 2003), and instrumented vehicle data (Lee et al., 2011) have shown that crash risk is highest early in licensure, declines rapidly for about six months (about 1000 miles), and then slowly for years before reaching stable, adult rates. This pattern of crash risk is consistent with the contentions that driving is a complex enterprise and safety competence develops only gradually with experience (Groeger, 2000; Keating and Halpern-Felsher, 2008). However, crash risk is not evenly distributed among novice drivers, most having no crashes, some having one, and a small percentage having several during the first year or so of licensure (Simons-Morton et al., 2011a; Simons-Morton et al., 2006b), suggesting that inexperience alone does not fully explain crash risk among novice drivers.

One possible explanation for the high rate of crashes among novice teenage drivers is the tendency for teenagers to drive in a relatively risky manner. Adolescents are thought to take more risks than adults in general (Steinberg, 2008) and with respect to driving (Williams, 2003). On average teenagers report relatively high levels of risky driving, but with notable variability (Simons-Morton et al., 2006a; 2006b). Survey and archival research indicate considerable heterogeneity in the distribution of other measures of risky driving, including traffic citations (Li et al., 2011; O'Malley and Johnston, 2003) and drinking and driving (Beerman et al., 1988; McCartt et al., 2002; O'Malley and Johnston, 2003), with many drivers experiencing no events, some one event, and a small percentage multiple events.

The advent of naturalistic driving methods using instrumented vehicles has made possible the continuous assessment of risky driving. In particular, accelerometers can assess elevated gravitational-force (g-force) events exerted by the vehicle during acceleration and turns (Dingus et al., 2006). Elevated g-force events due to relatively rapid acceleration and deceleration can be dangerous to the extent they reduce the amount of available time to respond to hazards and increase the potential for loss of vehicle control (Elvik, 2006; Wahlberg, 2004; 2007).

The Naturalistic Teenage Driving Study (NTDS), in which the vehicles of a sample of newly-licensed teenage drivers were equipped with accelerometers, GPS, and cameras, provided a unique opportunity to analyze elevated g-force event rates, here after called kinematic risky driving (Lee et al., 2011). In previous analyses of data from the NTDS we found three crash risk groups: (1) a group with very high crash risk that maintained throughout the study; (2) a group that started out with high crash risk but which declined rapidly after the first 6 months of driving; (3) and a low risk group that had few crashes over the 18-month study period (Guo et al., 2012). Using regression and ROC analyses we determined that the elevated g-force event rate in the past month was a good predictor of the likelihood of a crash/near crash in the following month (Simons-Morton et al., 2012). Basically, teenagers with high rates of kinematic risky driving, those whose general style of driving included a high rate of hard stops and sharp turns, were more likely to crash than teenagers low rates of kinematic risky driving, those whose driving style included few such events. In other analyses we determined that the rate of kinematic risky driving rates during the first 18 months of licensure were about 5 times higher among novice teenagers compared to their parents driving the same vehicles on the same roads and remained consistently high over the 18 month period (Simons-Morton *et al.*, 2011a). Also, rates were lower at night than during the day and with passengers than without and higher among teenage drivers with friends who engaged in higher rates of risky driving and other risky behavior such as substance use (Simons-Morton et al., 2011b).

The observed heterogeneity in individual crash/near crash trajectories suggested that the drivers might also be characterized according to kinematic risky driving groups. Specifically, we are interested in determining if there are particular subgroups with different underlying longitudinal profiles. Therefore, the purposes of the current analyses are to determine if (1) individuals can be classified with respect to risky driving; (2) patterns of risky driving are established in the first months of driving; and (3) individual factors explain the variability in kinematic risky driving. We hypothesize the following: H1. Patterns of kinematic risky driving observed during the first six months of driving will provide useful classification for the entire 18-month period. H2: Heterogeneity in individual trajectories of kinematic risky driving can be described by latent class models that postulate distinct risk groups. H3: Perceived driving risk, sensation/thrill seeking, driving privileges, and association with risky friends will contribute to kinematic risky driving classification.

2. METHOD

2.1. Participants

A sample of newly-licensed teenagers and at least one of their parents was recruited through driving schools and local media in Blacksburg and Roanoke area, Virginia, where teenagers can receive a provisional driver's license at the age of 16 years and three months. Identical twins and teenagers with Attention Deficit Disorder or Attention Deficit Hyperactivity Disorder were excluded from the study. The protocol was reviewed and approved by the Virginia Tech University Institutional Review Board. Parent consent and teen assent were obtained (additional details in Lee et al. (2011).

2.2. Vehicle Instrumentation

Vehicle instrumentation included a sophisticated driving data acquisition system designed at the Virginia Tech Transportation Institute (VTTI) (Dingus et al., 2006) that consisted of three-dimensional accelerometers, a global positioning system (GPS) receiver, and multiple video camera views recorders. The data were processed by the data acquisition system and stored in a hard drive installed in vehicle trunks. Cameras were installed strategically to continuously monitor the driver's face, the dashboard, and areas reachable by the driver's hands, and the forward and rearward roadway. Vehicles were instrumented within 3 weeks of provisional licensure (allowing unsupervised driving) and maintained for 18 months. Data were collected between June 2006 and September 2008.

2.3. Measures

2.3.1. Kinematic Risky Driving—G-force events were considered elevated when they exceeded the following thresholds: longitudinal deceleration/hard braking (≤ −0.45 g), longitudinal acceleration/rapid starts (≥ 0.35 g), lateral negative/left turn (≤ −0.50 g) and lateral positive/right turn (≥ 0.50 g) accelerations, and yaw rate (± 6 degrees per second). Yaw is a measure of correction after a turn and is calculated as the *delta v* between an initial turn and the correction. For analyses we created a composite variable made up of the five event rates that has a Cronbach's alpha (a measure of internal consistency) of 0.78 and is referred to hereafter as kinematic risky driving. This variable is identical to that used in previous analyses of data from this study, including the five categories of events and the thresholds at which events were counted (Simons-Morton *et al.*, 2011[ab], Simons-Morton et al., 2012).

2.3.2. Questionnaires—Surveys were administered four times, at baseline, 6-months, 12-months, and 18 months for each participant. Measures that were not expected to vary over time, such as sensation seeking and thrill and adventure seeking, were collected only at baseline. Measurements collected at the baseline survey were used in longitudinal latent class models and the average of the four data collections was used in logistic regression analyses. Measurement properties are shown in Table 1.

Sensation Seeking: The 8-item short form of the Sensation Seeking Scale Form V was administered at baseline (Zuckerman, 1994). For each item, participants have to choose between a lower and a higher sensation seeking statement (e.g., I like “wild” uninhibited parties vs. I prefer quiet parties with good conversation). The Cronbach’s alpha was 0.75 for the baseline short-form sensation seeking scale.

Thrill and Adventure Seeking: This variable is from the NEO personality inventory (Costa & McCrea, 1992). Examples of the 10 items include the following: “A sensible person avoids activities that are dangerous vs. I sometimes like to do things that are a little frightening”. The Cronbach’s alpha was 0.81 for the baseline thrill and adventure seeking scale.

Driving Privileges: This scale included 14 items about driving privileges from Simons-Morton et al (2006a) that asked “How often are you allowed to drive under the following conditions? Response options ranged from 1 (never) to 5 (any time I want)”. Examples of items include the following: after midnight; on high-speed roads; in bad weather; with two or more teen passengers; without telling your parents where you were going; etc. The Cronbach’s alpha was 0.88, 0.90, 0.86, and 0.88 for the four time periods, respectively.

Driving Risk Perceptions: This measure, used in previous studies on driving behavior (Hartos et al., 2002; Simons-Morton et al., 2006b), included 14 items that asked “How much risk for crash or injury do you think newly licensed teens have if they drive unsupervised in the following situations?” Examples of the situations include driving late at night, while not wearing a seat belt, in unfamiliar areas, with teenage passengers, under the influence of alcohol, and with passengers who had been drinking. Response options were low to high risk on a 1–5 scale. The Cronbach’s alpha was 0.85, 0.91, 0.90, and 0.85 for the four time periods, respectively.

Self-reported Risky Driving: The risky driving scale includes 15 items from Simons-Morton et al., (2006b; 2006a) that ask “How often in the past 7 days (response options 0–7) have you done the following things?” Examples of questions include: switched lanes to weave through traffic; cut in front of another vehicle to turn; went through an intersection when the light was red or just turning red; changed lanes without signaling. The Cronbach’s alpha was 0.82, 0.90, 0.91, and 0.89 for the four time periods, respectively.

Friends’ Risky Behavior (Risky Friends): This measure developed by Simons-Morton et al. (2006b) included the following seven items: “How many of your friends would you estimate … smoke cigarettes, drink alcohol, get drunk at least once a week, use marijuana, drive after having two or more drinks in the previous hour, exceed speed limits, and do not use safety belts (response options of none, a few, some, most, all)”. The Cronbach’s alpha for the seven-item friends’ risky behavior was 0.80, 0.90, 0.89, and 0.86 for the four time periods, respectively.

Friends' Risky Driving: This measure included the following three items on friends' risky driving: "How many of your friends would you estimate … drive after having two or more drinks in the previous hour, exceed speed limits, and do not use safety belts" (response options were none, a few, some, most, all) (Hartos et al., 2002; Simons-Morton et al., 2006b). The Cronbach's alpha for the three-item friends' risky driving was 0.59, 0.64, 0.62, and 0.57 for the four time periods, respectively.

2.4. Statistical Analyses

Individual longitudinal profiles (or trajectories) of kinematic risky driving were calculated. Average response rates (ARR) were employed as the measure of kinematic driving risk, calculated as the frequency of elevated g-force events divided by total miles driven. Tracking over time was examined by dividing study participants into groups based on each 6-month interval data (above and below the median), and exploring the individual trajectories over the 18-month follow-up period. In previous analyses using the same measure of kinematic risky driving used in the current study we found that one month prior was better than longer periods for predicting short-term risk of crash involvement (Simons-Morton et al., 2012). Other analyses of these data examined event rates over 3-month periods (Simons-Morton et al., 2011 a and b), which provided a reasonably stable measure that could be used to examine the patterns and variability of kinematic risky driving over the 18-month study period. In the current analyses we elected to use 6-month intervals to examine the "tracking" of kinematic measurement. Given the marked variation in kinematic count data, we *a prior* elected to examine 6-month intervals, which provided a highly stable measure and limited the impact of short-term variability on trajectories.]

A formal investigation of the profiles of risk groups was conducted using latent class models. To identify the presence and number of underlying classes, we fit several latent class Poisson models using R package flexmix. The outcome for these analyses was trip level composite events. The Akaike information criterion (AIC) was used to choose the number of latent classes, where the minimum AIC reflects the number of latent classes best supported by the data. Considering the small sample size, we fit uni-variable models containing one covariate in each model while adjusting for logarithm of miles driven, gender, and time since licensure (categorized into 6 quarters). The effects of covariates were tested with Z-tests using standard errors calculated with bootstrap method to account for correlation among individual longitudinal measurements (500 bootstrap samples were used). In latent Poisson models, individuals were assigned to either of the two latent classes because the posterior probabilities for class membership were near zero or one. Therefore, we further investigated the effects of covariates on latent groups using logistic regression. The class membership identified from the latent models was used as binary dependent variable and the average of covariates over 18 months as the independent variables.

Latent class models for longitudinal data allow investigators to identify different discrete risk groups with different trajectory patterns. With these models we can examine what factors classify an individual into one of these risk groups. In some sense, this analysis provides a way to explain and account for the marked heterogeneity among teen drivers. Latent class models have been used in many areas of behavioral, clinical, and epidemiologic studies. For example, latent class models have been used to examine the trajectory classes of prostate cancer (Lin et al., 2002) and criminal behavior (Kreuter & Muthen, 2008).

3. RESULTS

Study participants included 22 male (52.4%) and 20 female (47.6%) newly-licensed drivers with a mean age of 16.4, including 38 Caucasian, 3, and 1 other races (1 unreported).

3.1. Initial Data Analyses and Tracking By 6-month Period

We first graphically examined sample summary statistics to check for the evidence of risk classification, which is displayed in Figure 1 (a) – (c). If drivers had an ARR higher than the median in the 1st 6-months, we assigned them to higher risk group and then plotted their observed kinematic risky driving trajectories over the entire study period in the left subpanel of Figure 1 (a). We classified those with an ARR lower than the median in the 1st 6-months to the lower risk group and plotted their traces of ARR in the right subpanel of Figure 1 (a). Notably, the trajectories of the higher risk drivers in right subpanel tracked above the median, while the lower risk drivers in the left subpanel tracked below the median over the entire study period. We classified subjects similarly using the 2nd and 3rd 6-months of driving record shown in Figure 1 (b) and 1 (c) respectively. No matter which 6-month period was used to classify drivers, kinematic risky driving trajectories tended to be similar for the drivers in the same subpanel in terms of overall mean and variability and those in the lower-risk group were generally different from those in the higher-risk group. These results led us to utilize latent class approaches to model this tracking and determine associated factors.

3.2. Kinematic Risky Driving Classes

To investigate the appropriateness of the assumption of underlying kinematic risky driving groups, we initially fit latent class models without any covariates. The results indicate that a model with three latent classes described the data somewhat better than models with one or two latent classes; the AIC values were 112197, 99737, and 96425 for models with 1, 2, and 3 latent groups, respectively, where the minimum AIC reflects the best fitted model. However, there were only three individuals in the highest risk group; therefore, we focused subsequent analyses on models with one or two latent groups.

To better characterize the two groups determined by the model, we plotted the trajectories of kinematic event rates in each class. Figure 1 (d) shows that ARR's among one group (left subpanel) were generally lower than the ARR's in the other group (right subpanel), which suggests that latent classes correspond to driving risk groups. The trajectories from the latent class model, shown in (d), also followed a pattern of tracking for the entire 18-month study period and they were similar to but more stable than the observed values shown in (a) – (c).

We further examined the tendency for kinematic risky driving to track over time using measures of diagnostic accuracy such as sensitivity and specificity. Shown in Table 2 are the relationships between the latent model-based classes and the observed classes based on the median for each (6-month) period. Notably, of those classified as high-risk drivers in the latent class model, 88.9% had ARR above the median during the first 6-month period and 94.4% had ARR above the median in the 2nd and 3rd 6-month periods (i.e, sensitivity of the classifications based on the simple median relative to the risk group determined by latent class modeling). These results suggest that individual kinematic risky driving patterns persist over time. Further, a short 6-month interval reliably identified risk group with high accuracy.

3.3. Predictors of risky driving

For the one class model of kinematic risky driving (adjusted for the logarithm of miles driver, gender, and time since licensure), self-reported risky driving of the drivers, friends' risky driving, and friends' risky behaviors were significant factors (1 Class Model in Table 3). Perceptions about driving privileges and risky driving were marginally and negatively significant (e.g., greater perceptions of risk, lower kinematic risky driving). When we fit uni-variable models with two latent groups using the same adjusting variables, none of the factors were significantly associated with kinematic risky driving in either lower risk or higher risk group (2 Latent Class Model in Table 3). This suggests that once individuals are divided into low-risk versus high-risk groups, these factors do not explain the heterogeneity within the group

The latent class Poisson model just presented describes the short-term covariate effects, since it models the response for each trip. Next, we conducted binary logistic regression analyses to model long-term effects for latent risk group membership during the entire study period. As shown in Table 4, friends' risky driving was the only factor associated with a marginally significant association with drivers' grouping, indicating that long-term kinematic risky driving pattern of teen drivers may be influenced by friends' risky driving.

4. DISCUSSION

The availability of objective data from the NTDS in the form of elevated g-force events provided a unique opportunity to determine if kinematic risky driving over time among newly-licensed teenage drivers could be grouped according to risk trajectories and if assignment to group could be predicted with shorter observation periods (6 versus 18 months). The primary findings were that the data were well characterized by two groups, a higher and a lower risk group, and that kinematic risky driving tracked well according to the latent class model and the observed data for each 6-month period.

The three-class latent model best fit the data. However, the 3rd group with very high kinematic risky driving rates contained only 3 cases and was too small for analyses of co-variates and was not further considered. Perhaps such a group would emerge in analyses of a larger sample. This small group consisted of the highest risk drivers. Also, we expected but did not find evidence for a trajectory group whose kinematic risky driving rates declined over time, as we found for crash/near crash rates (Guo et al., 2012). The three crash/near crash groups included a high risk group that did not decline, a lower risk group that remained low, and a high risk group that declined after about 6-months. Guo and colleagues concluded that this last group learned from their driving experience how not to crash. While the novice teenage drivers in our sample got better with experience at not crashing, we did not find that they learned to drive in a less risky manner. One possible explanation for this finding is that novice teenage driving competence would be expected to increase over time, giving rise to greater confidence in their ability. This would be similar to other complex psycho-motor skills, for example, skiing, where some novices would be expected to be more aggressive than others and maintain this level of aggressiveness even as they take on more complex slopes.

The two-class model, with one lower risk and one higher risk class, fit the data well, as evidenced by Table 2 and Figure 1 (d), and the resulting classes were stable over time. Of drivers classified as higher risk according to the latent class trajectory analyses of data from the entire 18-month period, 88.9% were above the median during the first 6-month period and 94.4% were above the median in the 2nd and 3rd 6-month periods. While there was variability among the high and low risk groups, in general those in the lower risk group remained low and those in the higher risk group remained in that group over the entire 18 month study period, regardless of when they were first classified according to risk. One implication of tracking is that those who engage in high levels of risky driving during the first 6-months of licensure are likely to continue to engage in high risk driving and therefore are at elevated crash risk (Simons-Morton et al., 2012). It is now possible for parents to monitor risky driving using feedback devices based on accelerometers that are commercially available and it may be beneficial for parents of high-risk youth to avail themselves of this technology.

In addition to identifying risk classes or groups, the research sought to identify predictors of kinematic risky driving. Of the several variables examined, self-reported risky driving and risky friends emerged as predictors. The association between self-reported and kinematic risky driving suggests that it may be possible to identify those at high risk simply by asking them about how frequently they drive in a risky manner with respect to an index of driving behaviors. The relationship between risky friends and kinematic risky driving probably reflects social influence, which can occur directly in the form of peer pressure or indirectly in the form of social norms (Simons-Morton, McLeroy, & Wendel, 2011). Indeed, risky driving could be influenced by teenage drivers’ perceptions that their friends engage in risky behavior, even if they do not in actuality (Fleiter et al., 2010). However, these factors did not predict kinematic risky driving when the data were modeled assuming the presence of two risk groups, implying these covariates may be related to the classification of individuals into risk groups (long-range behavior), but not to changes in the outcomes given the risk group (short-term behavior).

Curiously, sensation seeking and thrill and adventure seeking, personality traits that would logically be associated with risky driving and which have sometimes been found to be associated with measures of risky driving were not significant in our analyses (Zuckerman, 2006). This may suggest that risky driving, when measured objectively using kinematic data, is more a style of driving than a self-reported personality characteristic. Also, we found only marginally significant association between kinematic risky driving and perceived risk, which has sometimes been linked to self-reported risky driving (Hatfield & Fernandes, 2009). Finally, we found marginally significant association with driving privileges, which is an indirect reflection of parental management of teenage driving.

The NTDS is the first study to report kinematic risky driving trajectories, but generalization of the findings is limited by the small sample recruited from a single region in Virginia.

We conclude that in our sample of novice teenage drivers kinematic risky driving during the first 6-month period tended to track over time within the lower and higher risky driving groups. Self-reported risky driving and having risky friends were predictors of kinematic risky driving, but these variables (risky friends was marginally significant) did not explain the heterogeneity within higher and lower classes of risky drivers.

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Highlights

- We assessed elevated g-force event rates, called kinematic risky driving, among novice teenage drivers using accelerometers, GPS, and other naturalistic driving methods.
- Rates during the first 6 months were similar to rates during the next two 6 month periods, suggesting substantial tracking.
- Risky driving over the 18-month study period was best characterized by two classes, a higher-risk and a lower-risk class.
- Self-reported risky driving and having risky friends were predictors of elevated g-force rates, but these variables (risky friends was marginally significant) did not explain the heterogeneity within higher and lower classes of risky drivers.

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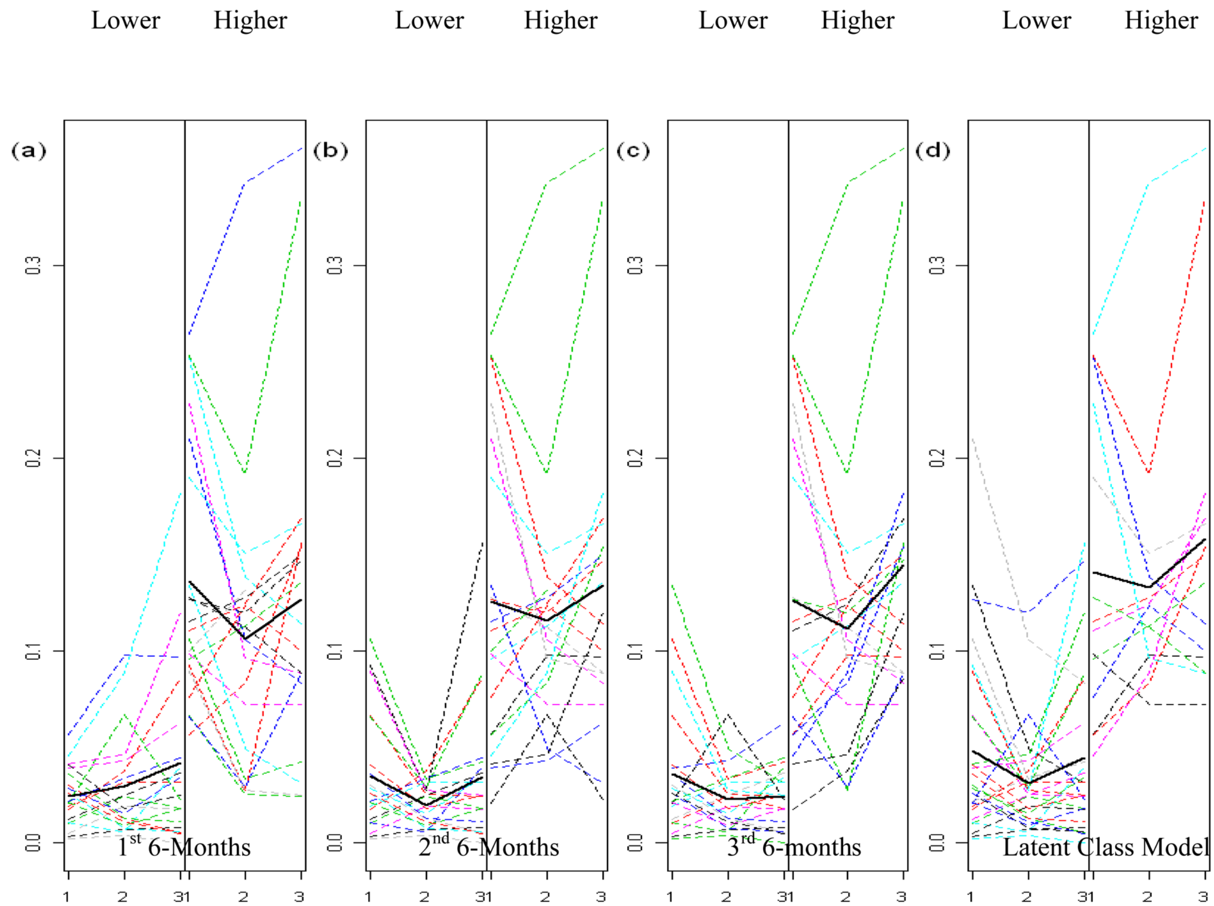

Figure 1.
Longitudinal trajectories of kinematic risky driving average response rates (ARR) over the 18-months of study. The average of all subjects' ARR's in each subpanel is plotted in black bold line.1, 2, and 3 on x-axis represent the first, second, and third 6-month intervals. Y axis marks ARR in each interval. Panels (a), (b), and (c) provide the observed trajectories of drivers classified as lower risk (left subpanel) if below the median and higher risk (right subpanel) if above the median for the 1st, 2nd, and 3rd 6-month period, respectively. Panel (d) includes trajectories of the lower and higher risk groups based on latent class model containing only intercepts (no co-variates).

Table 1

Distribution of covariates.

Variable (# Items)	Chronbach's Alpha	Mean (SD)	Min	Max
Sensation Seeking, short form[a] (8 items)	0.75	1.47 (0.29)	1.00	2.00
Thrill and adventure seeking[a] (10 items)	0.81	1.64 (0.29)	1.10	2.00
Driving privileges (14 items)	0.86–0.90	3.08 (0.63)	1.77	4.71
Perceptions about risky driving (14 items)	0.85–0.91	3.73 (0.42)	2.84	4.54
Self Reported Risky driving (19 items)	0.82–0.91	1.81 (0.39)	1.10	3.02
Friends' risky behavior (7 items)	0.80–0.90	1.09 (0.62)	0.04	3.04
Friends' risky driving (3 items)	0.57–0.64	1.16 (0.56)	0.00	3.25

[a]Sensation Seeking and Thrill and Adventure Seeking were measured at baseline. Other variables were measured at baseline, at 6 months, 12 months, and 18 months and averaged and the range of the Cronbach's Alphas was reported.

Table 2

Percent agreement in risk classification according to the latent model-based classes and the observed risk groups above (higher risk) and below (lower risk) the median during each 6-month period.

		Risk Groups Identified using ARR in 1st 6-months		Risk Groups Identified using ARR in 2nd 6- months		Risk Groups Identified using ARR in 3rd 6- months	
		HR	**LR**	**HR**	**LR**	**HR**	**LR**
Latent Classes	High Risk	88.9	11.1	94.4	5.6	94.4	5.6
	Low Risk	17.4	82.6	13.0	87.0	13.0	87.0

Table 3

Regression analyses of covariate associations with kinematic risky driving/6month period.

	1 Class Model		2 Latent Class Model			
			Higher risk		Lower risk	
Variable	Est (SE)[a]	P value	Est (SE)[a]	P value	Est (SE)[a]	P value
Gender	0.23 (0.38)	0.55	−1.16 (0.96)	0.23	1.84 (1.06)	0.08
Self reported risky driving	0.71 (0.37)	0.05	0.58 (0.53)	0.27	0.20 (0.62)	0.74
Perceptions on risky driving	−0.44 (0.24)	0.07	−0.53 (0.39)	0.17	−0.09 (0.57)	0.88
Driving privileges	0.50 (0.26)	0.06	0.51 (0.51)	0.31	−0.03 (0.62)	0.96
Friends’ risky driving	0.66 (0.20)	<0.01	0.45 (0.41)	0.27	−0.02 (0.62)	0.97
Friends’ risky behavior	0.66 (0.18)	<0.01	0.34 (0.34)	0.32	0.47 (0.43)	0.28
Sensation Seeking, short form	0.43 (0.67)	0.52	0.34 (1.91)	0.86	1.33 (1.45)	0.36
Thrill and adventure seeking	−0.71 (0.87)	0.42	−0.90 (2.07)	0.66	0.80 (1.79)	0.65

[a]Est and SE stand for parameter estimates and standard errors. Results for intercepts and adjusting factors (gender, log miles, and quarters) are not shown.

Table 4

Logistic regression analyses on group membership in risky driving groups.

Variable	EST (SE)	P value
Gender[a]	0.91 (0.64)	0.16
Self Reported Risky driving	0.19 (0.82)	0.82
Perceptions about risky driving	−0.38 (0.78)	0.62
Driving privileges	0.11 (0.57)	0.84
Friend’s risky driving	1.41 (0.75)	0.06
Friend’s risky behavior	0.40 (0.52)	0.44
Sensation Seeking, short form[a]	−1.64 (1.17)	0.16
Thrill and adventure seeking[a]	−1.70 (1.22)	0.16

[a]Gender, Sensation Seeking, and Thrill and adventure seeking were measured at baseline. Other variables were measured at baseline, at 6months, 12 months, and 18 months and averaged across time.