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Motor Vehicle Occupant Fatality Risk Based on Person-Time Exposed: Age, Sex, and Period of Week

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Abstract

During the 5 years from 2008 through 2012, motor vehicle crashes killed 34,091 people each year in the United States, on average, 23,783 (69.8) percent of whom were motor vehicle occupants. This study analyzes motor vehicle occupant fatality risk in terms of person-time exposed as a function of age, sex, period of week, and interactions of these factors. Results reveal strong circadian periodicities of occupant fatalities and fatality risk, with greater risk during late evening-early morning hours every day of the week and the greatest risk during Friday–Saturday and Saturday–Sunday evening-to-morning hours. But these circadian trends interact with age and sex whereby young male occupants exhibit the most fatalities and risk. The circadian variation in occupant fatality risk—across demographic age-sex populations, days of the week, and drunk- and nondrunk-driver-related fatal crashes – suggests a drowsiness component acting alone, and sometimes synergistically with alcohol, to impair the judgment and performance of motor vehicle occupants.

Introduction

During the 5 years from 2008 through 2012 (the last year for which final data are available)[1], motor vehicle crashes killed 34,091 people each year in the United States, on average, 23,783 (69.8) percent of whom were motor vehicle occupants (excluding motorcyclists) [1-3]. As a cause of death in the United States in 2009, traffic crashes ranked first among both 5–14 and 15–24 year olds, third among 1–4 year olds, and fifth among 25–44 year olds [4].

Motor vehicle occupant fatality risk is known to vary with a multitude of factors, e.g., occupant age, sex, personality, experience, day of week, time of day, location, weather, roadway type and design, vehicle type and size, safety equipment and use (e.g., seat belts), crash type and energy, nature and number of vehicle occupants and their relationship with the driver, speed, alcohol and/or drug impairment, driver distraction, risk taking, aggressive driving, road rage, dementia, drowsiness or fatigue, and myriad other factors [5–43].

Safety risk analysts typically define risk as a probability or rate with severity constant, such as risk of a type of vehicle crash (e.g., roll-over) or fatality (e.g., occupant). Such risks are compared via relative risks, risk ratios, or risk differences, often using multivariate modeling to assess comparisons and interactions while statistically controlling confounding covariates [e.g., 44-45]. But such definitions of risk, and the statistical models based on them, are fraught with challenges often neglected. The main problems fall into two categories.

First, analysts generally define risk as the rate of adverse event incidence per unit population, distance, or duration of exposure and implicitly assume that risk is uniform across times, places, and populations within exposure aggregates [46]. But if risk systematically varies across constituents of aggregates, then high- and low-risk constituents must appear less extreme, because aggregate risk is extrapolated to all constituents. Furthermore, since aggregate risk is a weighted average of constituent risks, where each weight is the proportion of exposure for a constituent, aggregate risk is biased against constituents with relatively less exposure.[2] If a small proportion of exposure entails the greatest risk, as generally occurs,[3] aggregate risk conceals that extreme risk. Yet high-risk constituents incur a large proportion of adverse

[1] Each year, the National Highway Traffic Safety Administration (NHTSA) releases preliminary crash fatality data for the prior year and final crash fatality data for the year before the prior year [2, p. 3].

[2] Given k arbitrarily defined constituents in an exposure aggregate, where f_j = adverse event incidence for constituent j, t_j = exposure for constituent j, and $r_j = f_j/t_j$ = risk for constituent j, the "average" aggregate risk is $r = \Sigma f_j/\Sigma t_j = (f_1/t_1)(t_1/\Sigma t_j) + (f_2/t_2)(t_2/\Sigma t_j) + \ldots + (f_k/t_k)(t_k/\Sigma t_j) = r_1(t_1/\Sigma t_j) + r_2(t_2/\Sigma t_j) + \ldots + r_k(t_k/\Sigma t_j)$.

[3] For example, crash risk in aviation is greatest during takeoffs and landings under instrument meteorological conditions at night, but exposure to these conditions is a relatively small fraction of total flight time or distance.

events,[4] so identifying them is necessary to effectively mitigate aggregate risk. Since risk is associated with myriad factors, such as those noted above, the identification of high-risk constituents requires high-dimensional multivariate data disaggregation.

Although detailed mishap data are often available (e.g., from incident reports or accident investigations), comparable exposure data are expensive and usually lacking [44, 47–49]. So analysts either omit exposure measures [50] or proffer risk estimates based on coarsely aggregated exposure data such as population size or miles traveled by a heterogeneous population of people or vehicles under diverse conditions over a long period of time and broad geographic area [1-3]. But neither of the latter approaches facilitates identification of risk extremes and effective countermeasures.

Second, risk analysts generally define risk as the ratio of adverse events to exposure, where exposure is a normalizing measure of opportunity for adverse events to occur:

risk = *adverse events* / *exposure*. Eq. 1

This definition of risk (Eq. 1) is alternately viewed as a probability, rate, or both [47-49; 51, pp. 3–9], revealing fuzziness in the concept of risk. But the main problem is that alternative measures of exposure lead to discrepant risk definitions and absurdity. Exactly the same event entails different "risks" depending on which denominator is used. And a risk comparison of two events may give *opposite* results depending on which denominator is used. The root of this confusion is that most risk exposure measures confound key covariates with risk.

For example, *person time* and *person distance* traveled are both regarded as appropriate exposure denominators for occupant fatality risk estimates and comparisons. But *person distance* is the product of speed and *person time*, so risk estimates and comparisons based on *person distance* are confounded with speed—a key covariate associated with mechanical energy and risk in all transportation domains. All else the same, risk comparisons based on *person distance* indicate lower risk for faster travel; e.g., at the extremes, pedestrian activity looks more risky, and space travel less, because "risk" measures based on person distance include speed in the exposure denominator.

Morris (2015) analyzed eight common measures of transportation fatality risk exposure (*person time*, *person distance*, *vehicle time*, *vehicle distance*, *population*, *registered vehicles*, *licensed drivers*, and *trips or operations*), showed they are all functions of *person time* exposed and (except *person time*) confounding covariates such as speed, and recommended *person time* as the exposure "denominator" for fatality risk estimates and comparisons within or across transportation modes (Table 1) [52]. Multivariate risk models express risk as a function of covariates to assess risk comparisons or interactions of interest while statistically controlling confounding covariates [c.f., 44–45]. But an inappropriate exposure denominator invalidates inferences by confounding risk with key covariates, e.g., speed, occupancy, and average person time exposed per population member, registered vehicle, licensed driver, or trip (Eqs. 3–9 in Table 1). Use of an inappropriate exposure denominator defeats the *normalizing* purpose of an exposure denominator required for valid risk comparisons.

Definitions of risk based on inappropriate exposure denominators reduce to absurdity.[5] For example, consider definition of fatality risk with *person distance* (Table 1, Eq. 3) as opposed to *person time* (Table 1, Eq. 2) as the exposure denominator. For obvious reasons (e.g., both crash rates and crash severity increase exponentially with speed [53]), car occupants moving at 100 mph experience more fatality risk than occupants at 50 mph, all else the same for any period of time. But unless risk based on *person time* is at least twice as high at 100 mph as compared to 50 mph, risk based on *person distance* must be *lower* at 100 mph than at 50 mph—an absurdity. If fatality risk based on *person time* at 100 mph is exactly twice that at 50 mph, then risk based on *person distance* is exactly the same at 100 mph as at 50 mph—an absurdity. In general, unless speed is constant (thus cancels out), a risk comparison based on distance traveled confounds speed and risk differences. The greater the speed discrepancy, the greater the bias. Imagine risk based on person distance for space travelers gradually accelerating toward the speed of light: as their speed increases, all else the same, their fatality risk diminishes—an astronomical absurdity. Or, for a more practical example, imagine a risk comparison based on person distance traveled for pedestrian activity versus space travel.

Finally, for an example available on a government website at the time of this writing, an actual risk comparison using total U.S. *population* as the exposure denominator (Table 1, Eq. 6) reports motor vehicle-related fatality risk 13 times *greater* than motorcycle-related fatality risk [54]. But there is far more *person time* exposed to motor vehicle occupancy than motorcycling in the United States, and a risk comparison based on person time would yield the opposite results, consistent with universally accepted reality. Such confounding is less obvious (but just as serious) with other popular transportation safety risk exposure denominators, e.g., vehicle distance, which confounds both speed and occupancy with risk (Table 1, Eq. 5) and thus obscures whether changes in fatalities per vehicle distance traveled reflect changes in risk, speed, occupancy, or interactions of these factors with each other and/or other factors.

[4] For example, a large fraction of all motor vehicle occupant fatalities involve (especially young) males traveling during early morning hours on Saturday and Sunday, a relatively high-risk but small region of motor vehicle occupant exposure space (see Figure 5).

[5] *Reduction to absurdity* is a time-honored logical argument method for proving the truth or falsity of propositions (e.g., see http://en.wikipedia.org/wiki/Reductio_ad_absurdum).

Table 1: Functional Measures of Transportation Fatality Risk

$$\frac{\text{fatalities}}{\text{person time}} = \text{risk} \qquad \text{Eq. 2}$$

$$\frac{\text{fatalities}}{\text{person distance}} = \frac{\text{risk}}{\text{speed}} \qquad \text{Eq. 3}$$

$$\frac{\text{fatalities}}{\text{vehicle time}} = \text{occupancy by time} \times \text{risk} \qquad \text{Eq. 4}$$

$$\frac{\text{fatalities}}{\text{vehicle distance}} = \frac{\text{occupancy by distance}}{\text{speed}}\ \text{risk} \qquad \text{Eq. 5}$$

$$\frac{\text{fatalities}}{\text{population}} = J \times \text{risk} \quad (J = \text{person time/population}) \qquad \text{Eq. 6}$$

$$\frac{\text{fatalities}}{\text{registered vehicles}} = K \times \text{risk} \quad (K = \text{person time/registered vehicles}) \qquad \text{Eq. 7}$$

$$\frac{\text{fatalities}}{\text{licensed drivers}} = L \times \text{risk} \quad (L = \text{person time/licensed drivers}) \qquad \text{Eq. 8}$$

$$\frac{\text{fatalities}}{\text{trips}} = M \times \text{risk} \quad (M = \text{person time/trips}) \qquad \text{Eq. 9}$$

SOURCE: Morris CC. Concept and measurement of transportation fatality risk. Bureau of Transportation Statistics. U.S. Department of Transportation. Washington, DC; 2015

Objectives

The present study assesses motor vehicle occupant fatality risk based on occupant hours of travel as a function of occupant age, sex, and period of week using U.S. data for 2009. Pedestrians, pedal cyclists, motorcyclists, occupants of buses and large trucks, and occupants under 5 years of age were excluded due to lack of corresponding travel data for those populations.

The primary measure of fatality risk is occupant fatalities per million occupant hours of travel (exposure). The amount of time people are exposed to a hazard (e.g., occupancy of a moving motor vehicle by a 20 year old male between midnight and 3:00 am Sunday morning) is a natural measure to normalize the incidence of adverse events (e.g., occupant fatalities) related to that hazard and facilitate comparisons of that risk to others across a broad spectrum of hazard domains. Estimates of minor, serious, and fatal motor vehicle occupant injury risk by age and sex based on both population size and occupant hours are also presented for comparison.

Methods

The 2009 National Household Travel Survey (NHTS) provides detailed data on motor vehicle occupant travel in the United States [55–56]. In this nationally representative survey of U.S. households, respondents provided information about themselves and trips they made during a designated travel day shortly before they were contacted in the survey. Respondents provided their age, sex, day of trip, trip start and end times, and other information. Survey data were weighted to provide estimates for all trips made by all noninstitutionalized persons over 5 years of age in the United States during 2009.

The data sources in the present study are:

(a) Estimated U.S. motor vehicle occupant hours of travel data by age, sex, and period of week (day of week and time of day) from the 2009 National Household Travel Survey (NHTS), a nationally representative survey of U.S. households [55–56];

(b) Estimated U.S. population by age and sex for 2009 from the U.S. Census Bureau via the Web-based Injury Statistics

Query and Reporting System (WISQARS) maintained by the Centers for Disease Control [57];

(c) Motor vehicle occupant fatalities (excluding occupants of motorcycles, buses, and large trucks) for 2009 from the Fatality Analysis Reporting System (FARS) maintained by the National Highway Traffic Safety Administration, a database of information about the scenarios, vehicles, drivers, and passengers involved in all fatal motor vehicle crashes on public highways and roads in the United States [58]; and

(d) Estimated unintentional, traffic-related (on public highway), motor vehicle occupant injuries from the National Electronic Injury Surveillance System All-Injury Program (NEISS-AIP), a probability sample of U.S. emergency room hospitals maintained by the U.S. Consumer Product Safety Commission in cooperation with the U.S. Centers for Disease Control [59].

In the present study, risk of motor vehicle occupant injury or death is defined as occupant injuries or fatalities per million occupant hours of travel and, where feasible for comparison, per 100,000 population members. Because travel estimates are not available for occupants less than 5 years old, these young occupants are excluded from all analyses.

Injuries are defined as *minor* if the victim was treated and released, held for observation, or left the emergency room before treatment; *serious* if the victim was hospitalized or treated and transferred to another facility; and *fatal* if the victim died within 30 days of the trauma as a result of the trauma. These operational definitions of injuries and fatalities are objective and codify substantial differences in the degree of trauma sustained, but are not universal. There are no universal definitions of injury trauma. Alternative and multivariate definitions of injury and trauma impact, e.g., in terms of body part or organ system, diagnosis, disposition, impact on (quality) life expectancy, and so on, are beyond the scope of this paper.

The statistical significance of differences and quantitative trends in estimated risk is assessed via analysis of deviance based on hierarchical quasi-likelihood generalized linear models relating the natural log of risk (the incident measure divided by the exposure measure) to covariates of interest, e.g., sex (dummy or effects coded), age (linear, quadratic, and cubic components of age coded via power polynomials), and the age by sex interaction (set of pairwise products of the age and sex codes). The generalized linear model scale parameter was estimated by the full model deviance divided by degrees of freedom. See Morris (2009) for more details and references on the statistical methodology [45]. Higher order interaction terms were assumed to reflect only nonsystematic (random) variation and omitted from regression models to increase degrees of freedom and statistical power. For tests of the statistical significance of generalized linear model coefficients (β_j) in each hierarchical analysis of deviance, the null hypothesis was $\beta_j = 0$, and the type I error criterion was .05 based on the *F* distribution.

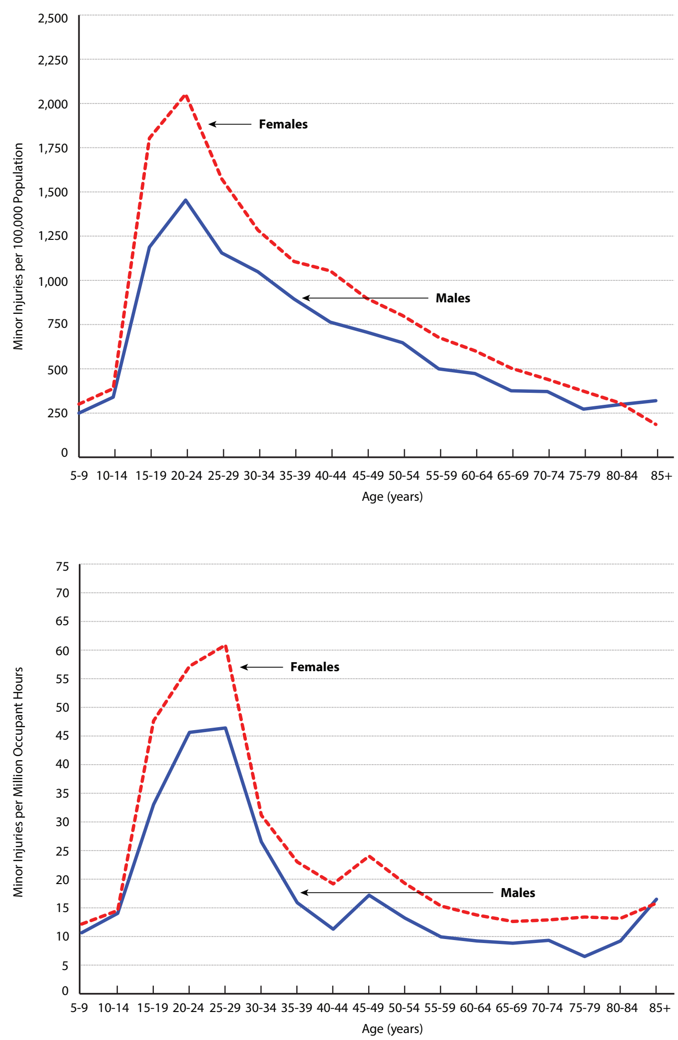
Results

Risk of Minor, Serious, or Fatal Occupant Injury by Age and Sex

Figures 1–3 give the estimated risk of minor (Figure 1), serious (Figure 2), or fatal (Figure 3) motor vehicle occupant injury by age group and sex with either population size (top panel) or occupant hours of travel (bottom panel) measuring exposure. With minor exceptions, and a difference in scale, the forms of the estimated risk distributions were similar for these two exposure measures at each risk severity level, i.e., minor, serious, or fatal injury.

As shown in both panels of Figure 1, the risk of minor injury was greater for female than male occupants for occupants under 80 years of age with either population size (p=.026) or

Figure 1: Risk of Minor Occupant Injury Per 100,000 Population Members (top panel) and Per Million Occupant Travel Hours (bottom panel) by Age and Sex in 2009



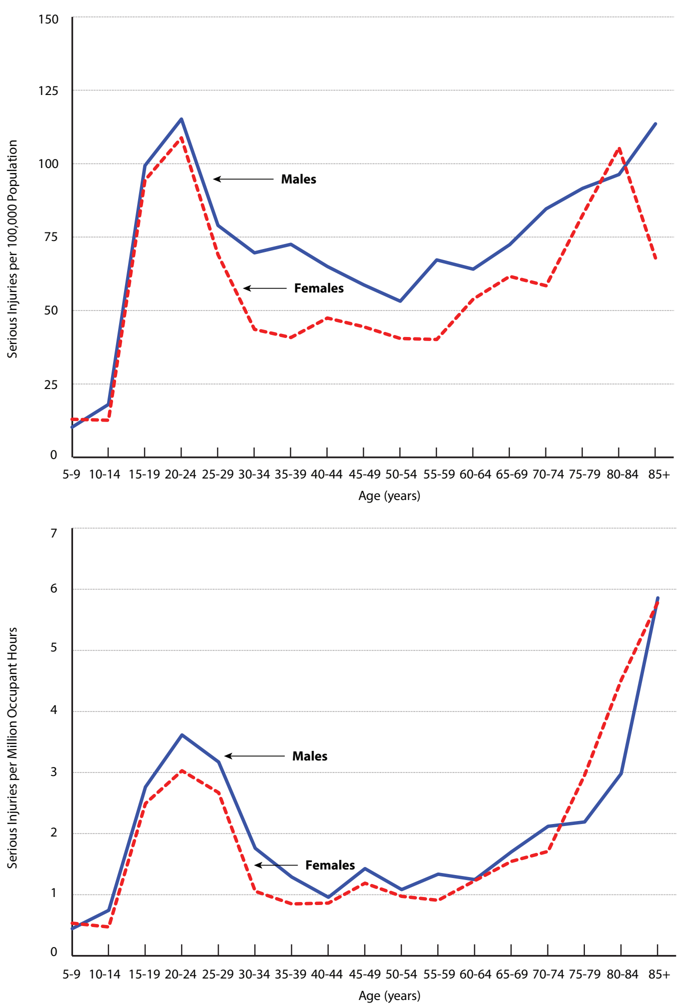
SOURCES: Centers for Disease Control (WISQARS website); Federal Highway Administration, National Household Travel Survey; and Bureau of Transportation Statistics, 2012.

occupant hours of travel (p=.008) as the exposure measure. In addition, whether risk exposure was defined in terms of population size or occupant hours of travel, the risk of minor injury was greatest for younger motor vehicle occupants, rising steeply from 15 years of age through 25 to 29, then declining and leveling off until about 80 years of age. Regardless of the exposure measure (population size, occupant hours), there were significant linear (p=.0002, p<.0001), quadratic (p<.0001, p=.011), and cubic (p<.0001, p<.0001) trend components in the association of risk with age, and none of these trend components interacted with sex.

As shown in both panels of Figure 2, the risk of serious injury appeared slightly greater for male occupants, but in fact, whether population size (top panel) or occupant hours of travel (lower panel) was the exposure measure, there was no significant sex effect, and no interaction of the linear, quadratic, or cubic components of age with sex. And there was no significant linear age effect whether population size or occupant hours of travel was the exposure measure. There was a significant quadratic age effect, but only with the occupant hours exposure measure (p=.011). Finally, there was a significant cubic age effect with either population size (p=.0008) or occupant hours (p<.0001) as the exposure measure, which confirms the most salient pattern in both panels of Figure 2 whereby serious injury risk increases dramatically from 10 to 20–24 years of age, declines and levels out from about 30–60 years of age, and then begins rising again to levels as great or greater than those in the early 20s.

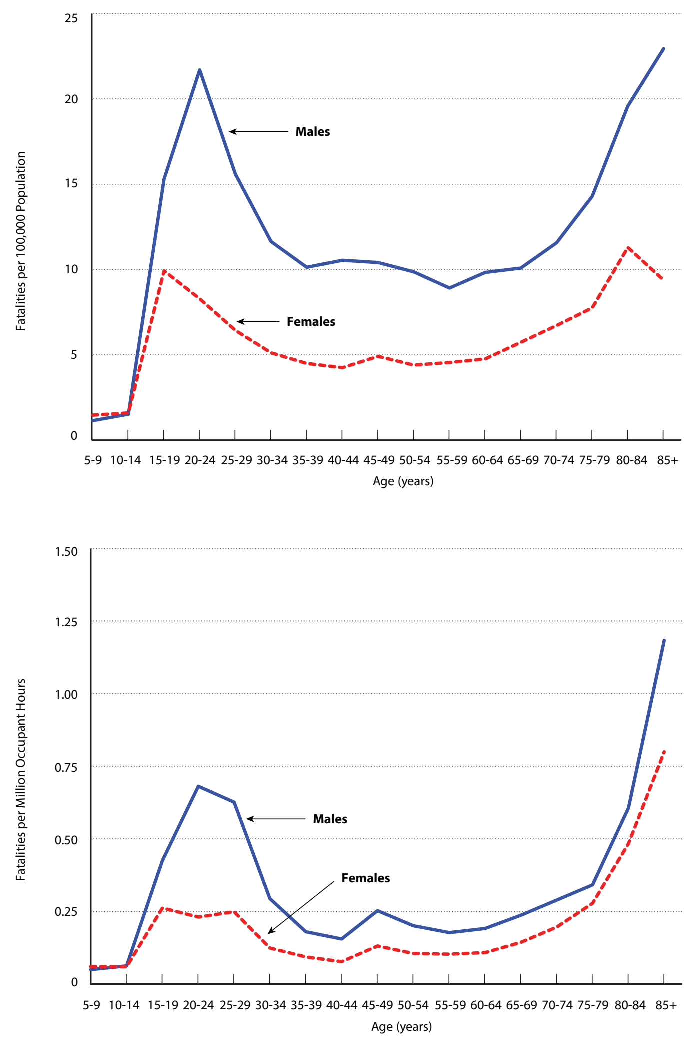
As shown in both panels of Figure 3, regardless of exposure measure (population size, occupant hours), the risk of fatal injury was significantly greater for male occupants (p<.0001,

Figure 2: Risk of Serious Occupant Injury Per 100,000 Population Members (top panel) and Per Million Occupant Travel Hours (bottom panel) by Age and Sex in 2009



SOURCES: Centers for Disease Control (WISQARS); Federal Highway Administration, National Household Travel Survey; and Bureau of Transportation Statistics, 2012.

Figure 3: Risk of Fatal Occupant Injury Per 100,000 Population Members (top panel) and Per Million Occupant Travel Hours (bottom panel) by Age and Sex in 2009



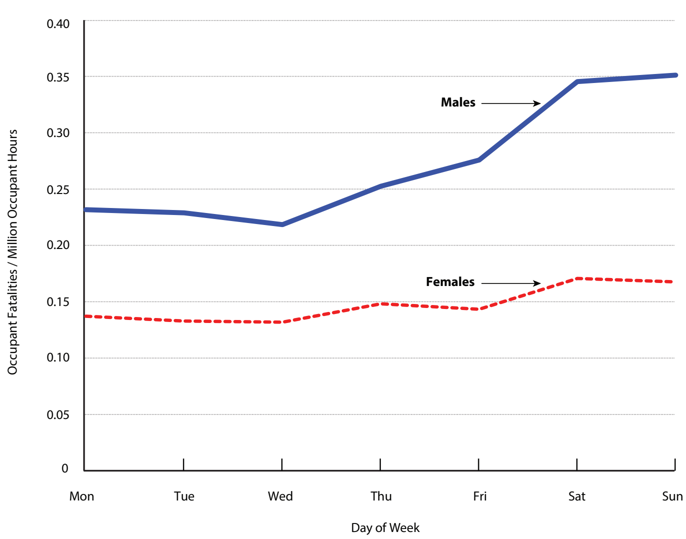
SOURCES: National Highway Traffic Safety Administration (FARS); Centers for Disease Control (WISQARS); Federal Highway Administration, National Household Travel Survey; and Bureau of Transportation Statistics; 2012.

p=.0006). There was no significant linear age effect whether population size or occupant hours of travel was the exposure measure. There was a significant quadratic age effect, but only with occupant hours as the exposure measure (p=.014). Finally, there was a significant cubic age effect with either population size (p<.0001) or occupant hours (p<.0001) as the exposure measure, which confirms the salient pattern in both panels of Figure 3 whereby fatal injury risk increases sharply from 10 to 20–24 years of age, declines and levels out from 30–60 years of age, then begins rising again to levels as great or greater than those in the early 20's. There was no significant interaction of the linear, quadratic, or cubic components of age with sex, confirming similar quantitative age effects for both sexes.

Risk of Fatal Occupant Injury by Sex and Period of Week

Motor vehicle occupant fatality risk increases on weekends, beginning Thursday, and is greatest on Saturday and Sunday for both males and females (Figure 4). Such temporal patterns of risk obviously cannot be identified using population size to measure exposure, because population size is constant across the temporal covariates (day of week, time of day) strongly associated with risk. The following analyses define risk in terms of occupant hours of exposure, and for brevity of expression, adopt the abbreviation *fpm* to denote occupant fatalities per million occupant hours. While the risk patterns in Figure 4 are interesting, they also mislead, because motor vehicle occupant fatality risk varies systematically with period of week, i.e., both day of week and time of day, and the greatest risks that certain populations of males and females experience during certain periods of the week are far greater than those shown in Figure 4.

Figure 4: Occupant Fatalities Per Million Occupant Hours by Sex and Day of Week From Monday Through Sunday in 2009



SOURCE: National Highway Traffic Safety Administration (FARS); Federal Highway Administration, National Household Travel Survey; and Bureau of Transportation Statistics, 2012.

To analyze risk as a function of period of the week, consider the eight 3-hour periods each day starting at midnight (0000–0300, 0300–0600, 0600–0900, 0900–1200, 1200–1500, 1500–1800, 1800–2100, and 2100–0000). Define *period of week* as the sequence of these periods from Monday through Sunday. Figure 5 gives occupant fatalities (top), hours of travel (middle), and fatalities per million occupant hours (bottom) by sex and period of week in 2009. Vertical lines mark midnight. Males' peak risk of 6.49 fpm during the period 12:00–3:00 am on Saturday morning (Figure 5, bottom) is about 19 times their "average" Saturday risk of 0.35 fpm (Figure 4). Figure 5 shows substantially higher risks than the average daily risks in Figure 4 for every other late-evening/early-morning period of the week, not just those on weekends. Nevertheless, Figure 5 also misleads because occupant fatality risk varies substantially not only with occupant sex and period of week, but also with occupant age as shown above in Figure 3. The following analyses disaggregate the fatality and hours of travel data by occupant age, sex, and period of week to more accurately estimate and compare motor vehicle occupant fatality risk.

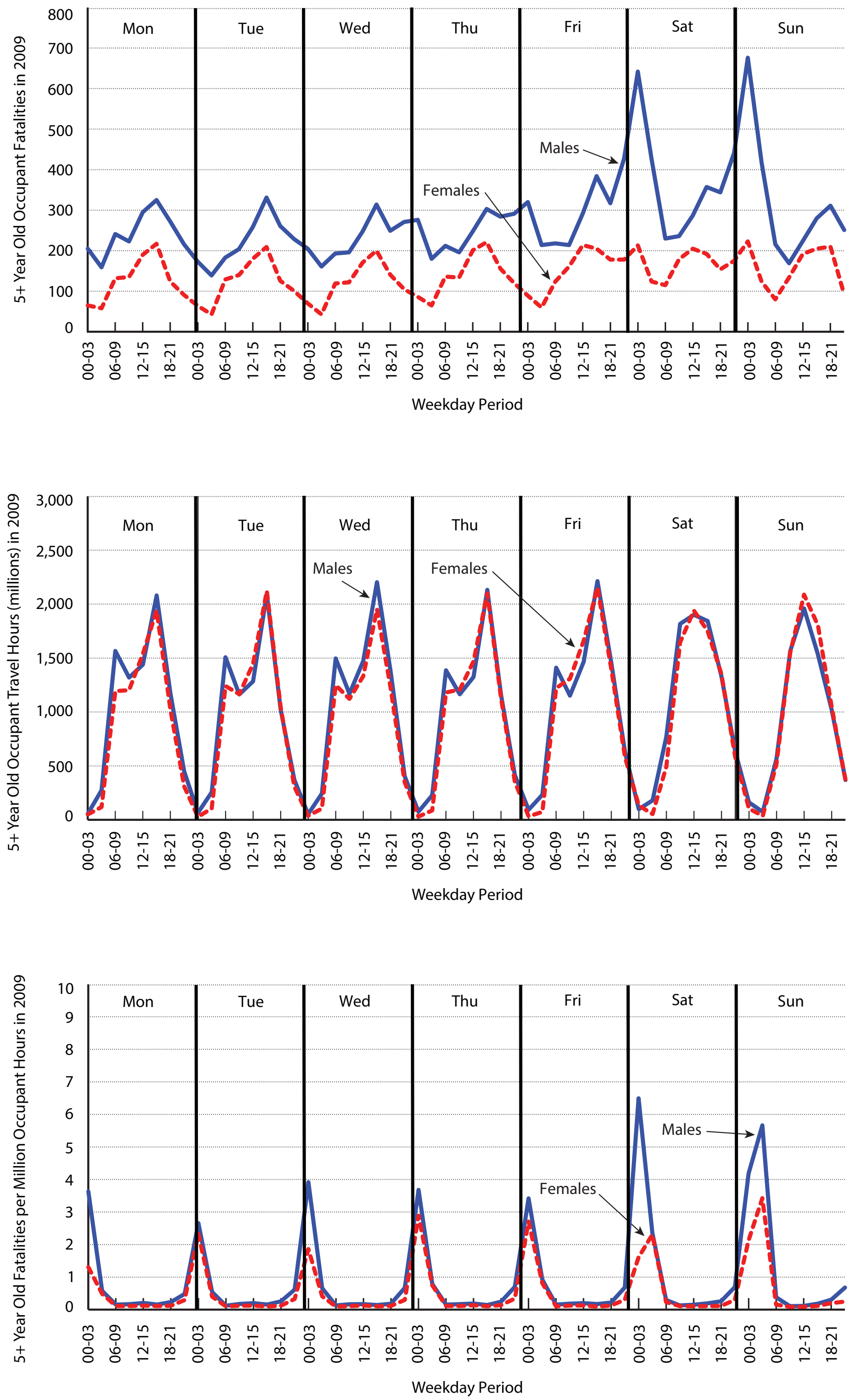
Risk of Fatal Occupant Injury by Age, Sex, and Period of Week

Figures 6–12 give occupant fatality risk in 2009 by sex and period of week for age groups 15–19, 20–29, 30–39, 40–49, 50–59, 60–69, and 70+ years. Risk is strongly circadian[6] for both sexes in all age groups. To facilitate age comparisons, Figures 6–12 use the same risk scale (0–25 fpm). To facilitate inferential statistical analysis of the circadian data in Figures 6–12, each *day* was defined to begin and end at noon instead of midnight, with day 1 beginning at noon Sunday and ending at noon Monday, day 2 beginning at noon Monday and ending at noon Tuesday, etc. Similarly, *period of day* was defined as the sequence of eight 3-hour periods in such a day, beginning at noon, as defined above. Defining *day* this way simplifies modeling the circadian variation in risk across the week via orthogonal polynomial coding of the linear and quadratic components of *day* and *period of day* thereby reducing model complexity and increasing degrees of freedom and statistical power. To further reduce model complexity, the risk data in each of Figures 6–12 were analyzed via separate hierarchical quasi-likelihood generalized linear regression models relating the natural log of fatality risk to the covariates: sex (dummy coded), day (linear and quadratic components coded via orthogonal polynomials), period of day (linear and quadratic components coded via orthogonal polynomials), day by sex, period of day by sex, and period of day by day.

Figure 6 gives occupant fatality risk by sex and period of week for 15–19 year olds. The peak risk of 20.0 fpm for males during the 3:00–6:00 am period Sunday morning

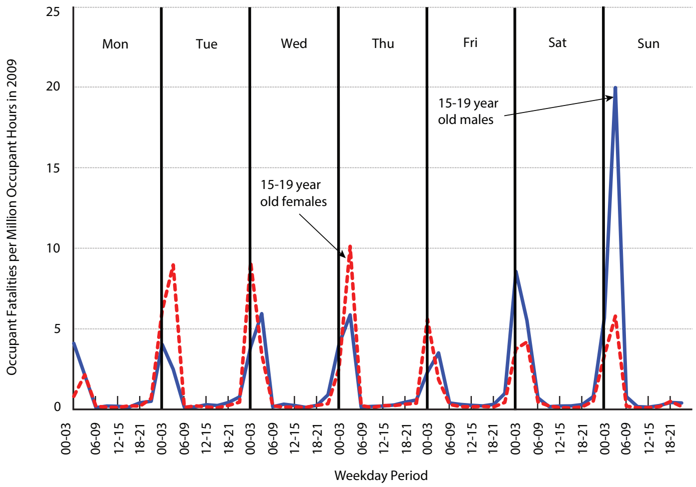
[6] *Circadian* here means "being, having, characterized by, or occurring in approximately 24-hour periods or cycles (as of biological activity or function)" and does not denote or imply involvement of the *circadian rhythm* or biological clock (downloaded on 11 June 2012 at http://www.merriam-webster.com/dictionary/circadian).

Figure 5: Occupant Fatalities (top), Hours of Travel (middle), and Fatalities Per Million Occupant Hours (bottom) by Sex and Period of Week From Monday Through Sunday in 2009



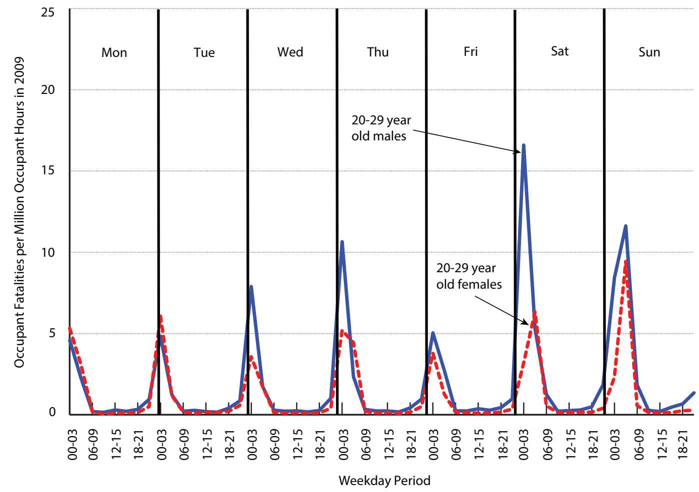
SOURCES: National Highway Traffic Safety Administration (FARS); Federal Highway Administration, National Household Travel Survey; and Bureau of Transportation Statistics, 2012.

Figure 6: 15- to 19-Year-Old Motor Vehicle Occupant Fatality Risk by Sex and Period of Week in 2009



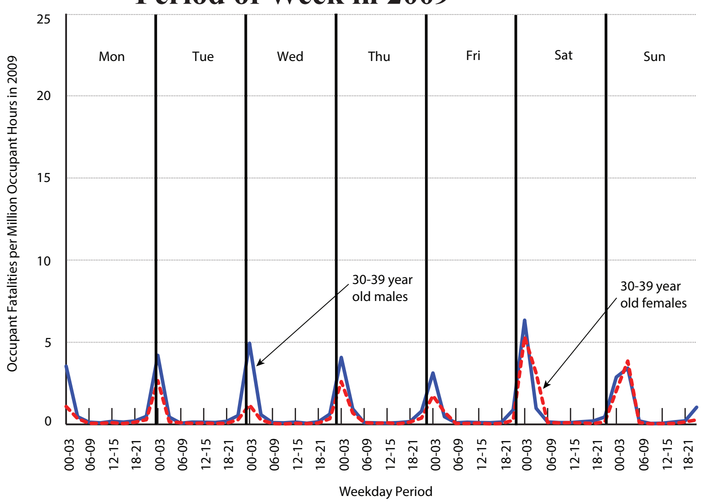
SOURCES: National Highway Traffic Safety Administration (FARS); Federal Highway Administration, National Household Travel Survey; and Bureau of Transportation Statistics, 2012.

Figure 7: 20- to 29-Year-Old Motor Vehicle Occupant Fatality Risk by Sex and Period of Week in 2009



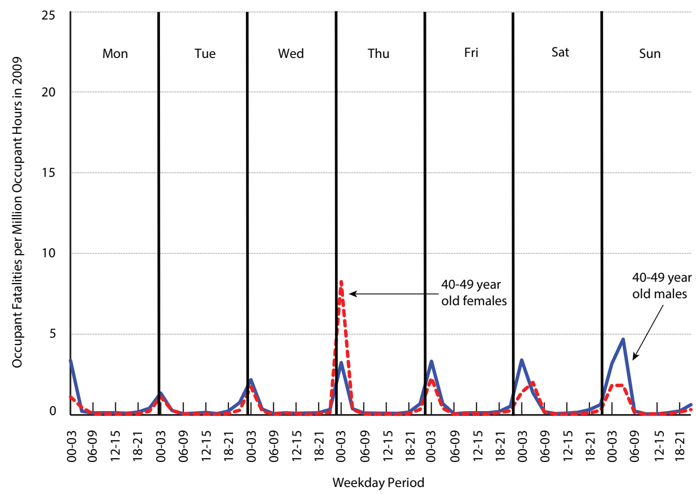
SOURCES: National Highway Traffic Safety Administration (FARS); Federal Highway Administration, National Household Travel Survey; and Bureau of Transportation Statistics, 2012.

Figure 8: 30- to 39-Year-Old Motor Vehicle Occupant Fatality Risk by Sex and Period of Week in 2009



SOURCES: National Highway Traffic Safety Administration (FARS); Federal Highway Administration, National Household Travel Survey; and Bureau of Transportation Statistics, 2012.

Figure 9: 40- to 49-Year-Old Motor Vehicle Occupant Fatality Risk by Sex and Period of Week in 2009



SOURCES: National Highway Traffic Safety Administration (FARS); Federal Highway Administration, National Household Travel Survey; and Bureau of Transportation Statistics, 2012.

is about 36 times the average Sunday risk of 0.56 fpm for this age-sex cohort. Similarly, the peak risk of 10.1 fpm for females during the 3:00–6:00 am period Thursday morning is about 33 times the average Thursday risk of 0.30 fpm for this age-sex cohort. Fatality risk was greater for male versus female occupants (p=.006). There was a linear day effect (p=.034) with risk increasing over the week. There was also a linear period of day effect (p=.008) (risk was higher in the latter part of the day as defined above). As expected given the highly circadian risk pattern, there was a quadratic period of day effect (p<.0001). There were no significant interactions, indicating similar day and period of day trends across males and females and similar period of day trends across days.

Figure 7 gives occupant fatality risk by sex and period of week for 20–29 year olds. The peak risk of 16.6 fpm for males during the 12:00–3:00 am period Saturday morning is about 16 times the average Saturday risk of 1.1 fpm for this age-sex cohort. Similarly, the peak risk of 9.4 fpm for females during the 3:00–6:00 am period Sunday morning is about 27 times the average Sunday risk of 0.35 fpm for this age-sex cohort. Fatality risk was greater for male versus female occupants (p<.0001). There was a linear day effect (p=.0007) with risk increasing over the week. There was also a linear period of day effect (p=.001) (risk was higher in the latter part of the day as defined above). As expected, there was a quadratic period of day effect (p<.0001). There were no significant interactions with sex, indicating similar day and period of day trends across males and females. There was a significant linear period of day by linear day interaction (p=.006), suggesting that the risk distribution shifted to later in the day as the week progressed.

Figure 8 gives occupant fatality risk by sex and period of week for 30–39 year olds. The peak risk of 6.3 fpm for males during the 12:00–3:00 am period Saturday morning is about 22 times the average Saturday risk of 0.29 fpm for this age-sex cohort. Similarly, the peak risk of 5.3 fpm for females during the 12:00–3:00 am period Saturday morning is about 37 times the average Saturday risk of 0.15 fpm for this age-sex cohort. Fatality risk was greater for male versus female occupants (p<.0001). And, as expected, there was a quadratic period of day effect (p<.0001). There were no other significant effects or interactions.

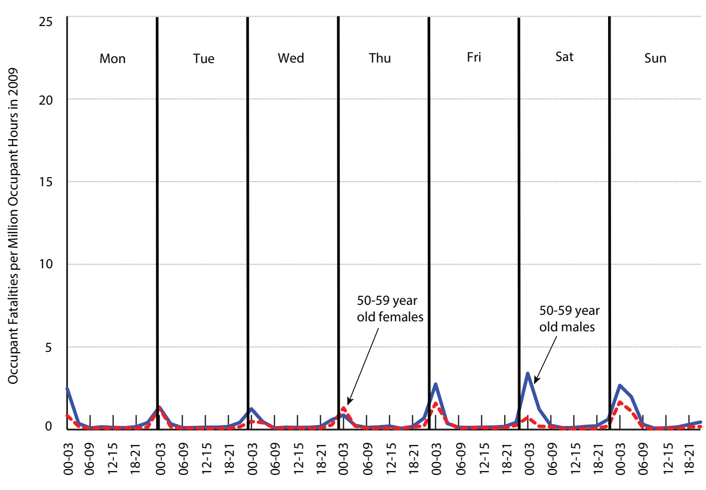
Figure 9 gives occupant fatality risk by sex and period of week for 40–49 year olds. The peak risk of 4.7 fpm for males during the 3:00–6:00 am period Sunday morning is about 19 times the average Sunday risk of 0.24 fpm for this age-sex cohort. The peak risk of 8.3 fpm for females during the 12:00–3:00 am period Thursday morning is about 96 times the average Thursday risk of 0.09 fpm for this age-sex cohort. Fatality risk was greater for male versus female occupants (p<.0001). There was a linear day effect (p=.035) with risk increasing over the week. As expected, there was a quadratic period of day effect (p<.0001). There were no other significant effects or interactions.

Figure 10 gives occupant fatality risk by sex and period of week for 50–59 year olds. The peak risk of 3.4 fpm for males during the 12:00–3:00 am period Saturday morning is about 14 times the average Saturday risk of 0.24 fpm for this age-sex cohort. The peak risk of 1.7 fpm for females during the 12:00–3:00 am period Sunday morning is about 15 times the average Sunday risk of 0.11 fpm for this age-sex cohort. Fatality risk was greater for male versus female occupants (p<.0001). As expected, there was a quadratic period of day effect (p<.0001). There were no other significant effects or interactions.

Figure 11 gives occupant fatality risk by sex and period of week for 60–69 year olds. The peak risk of 3.4 fpm for males during the 12:00–3:00 am period Friday morning is about 15 times the average Friday risk of .23 fpm for this age-sex cohort. The peak risk of 2.5 fpm for females during the 12:00–3:00 am period Saturday morning is about 21 times the average Saturday risk of 0.11 fpm for this age-sex cohort. Fatality risk was greater for male versus female occupants (p<.0001). As expected, there was a quadratic period of day effect (p<.0001). There was also a significant quadratic period of day by sex interaction (p=.021). There were no other significant effects or interactions.

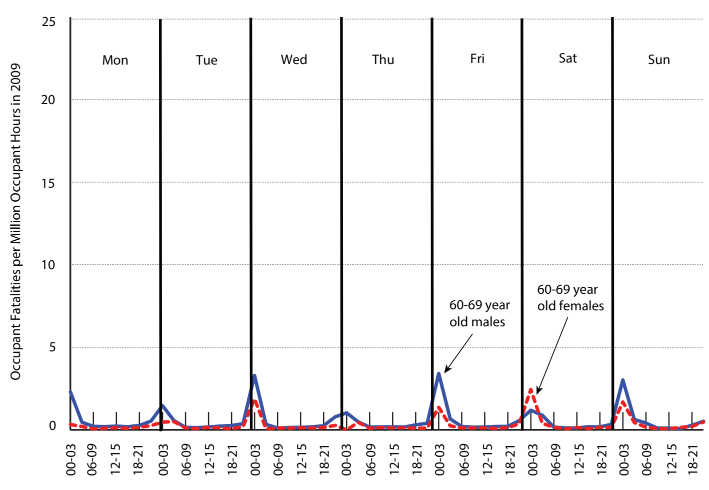
Figure 12 gives occupant fatality risk by sex and period of week for 70+ year olds. As shown above in Figure 3, fatality risk increases in the 70+ age group as compared to younger occupants, but the smaller population size of this age group increases variability in both fatalities and estimated travel time, and thus in estimates of fatality risk.

Figure 10: 50- to 59-Year-Old Motor Vehicle Occupant Fatality Risk by Sex and Period of Week in 2009



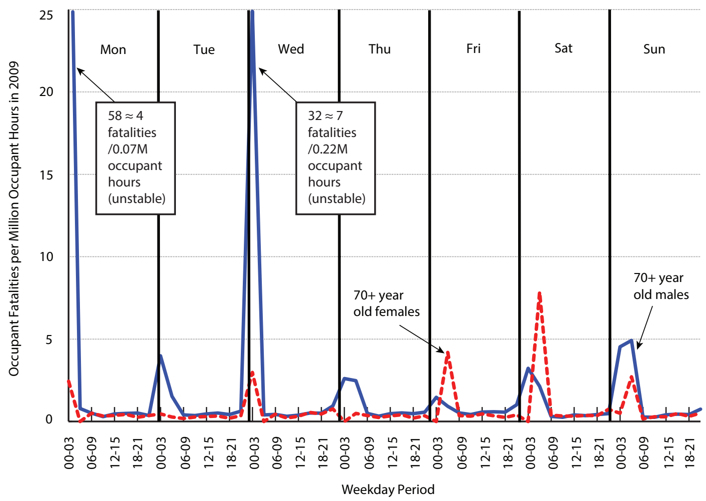
SOURCES: National Highway Traffic Safety Administration (FARS); Federal Highway Administration, National Household Travel Survey; and Bureau of Transportation Statistics, 2012.

Figure 11: 60- to 69-Year-Old Motor Vehicle Occupant Fatality Risk by Sex and Period of Week in 2009



SOURCES: National Highway Traffic Safety Administration (FARS); Federal Highway Administration, National Household Travel Survey; and Bureau of Transportation Statistics, 2012.

Figure 12: 70+ Year-Old-Motor Vehicle Occupant Fatality Risk by Sex and Period of Week in 2009



SOURCES: National Highway Traffic Safety Administration (FARS); Federal Highway Administration, National Household Travel Survey; and Bureau of Transportation Statistics, 2012.

Nevertheless, a strong circadian periodicity of occupant fatality risk is apparent in Figure 12 for this age group as well. Fatality risk was greater for male versus female occupants (p=.0002). There was a linear period of day effect (p=.002). And, as expected, there was a quadratic period of day effect (p<.0001). There were no other significant effects or interactions.

Risk of Fatal Occupant Injury by Drunk-Driver Relatedness and Period of Week

Figure 13 gives occupant fatalities (top panel) and fatalities per million occupant hours of travel (bottom panel) by drunk-driver-relatedness and period of week in 2009. This analysis partitions occupant fatalities based on whether or not the crash was determined to involve a drunk-driver (whether or not the fatally injured occupants or driver of their car was drunk). Dividing those fatalities, respectively, by occupant hours of travel yields the risks, respectively, of drunk- or nondrunk-driver-related occupant fatality. Note that these risks have nothing to do with the risks of occupant fatality while the driver of the occupant's vehicle is either drunk or not, which risks cannot be estimated because whether the driver was drunk or not is not queried (and would be suspect even if it were) in the NHTS source of occupant travel data. Both drunk- and nondrunk-driver-related occupant fatalities exhibit strong circadian periodicities, but out of phase, with drunk-driver-related fatalities peaking just after midnight and nondrunk-driver-related fatalities peaking just after midday. Also, while drunk-driver-related fatalities steadily increase over the week, with sharp increases early Saturday and Sunday, nondrunk-driver-related fatalities remain about the same Monday through Friday and decline on Saturday and Sunday (top panel). Nevertheless, both drunk- and nondrunk-driver-related occupant fatality risk peaks in the early morning hours after midnight (bottom panel).

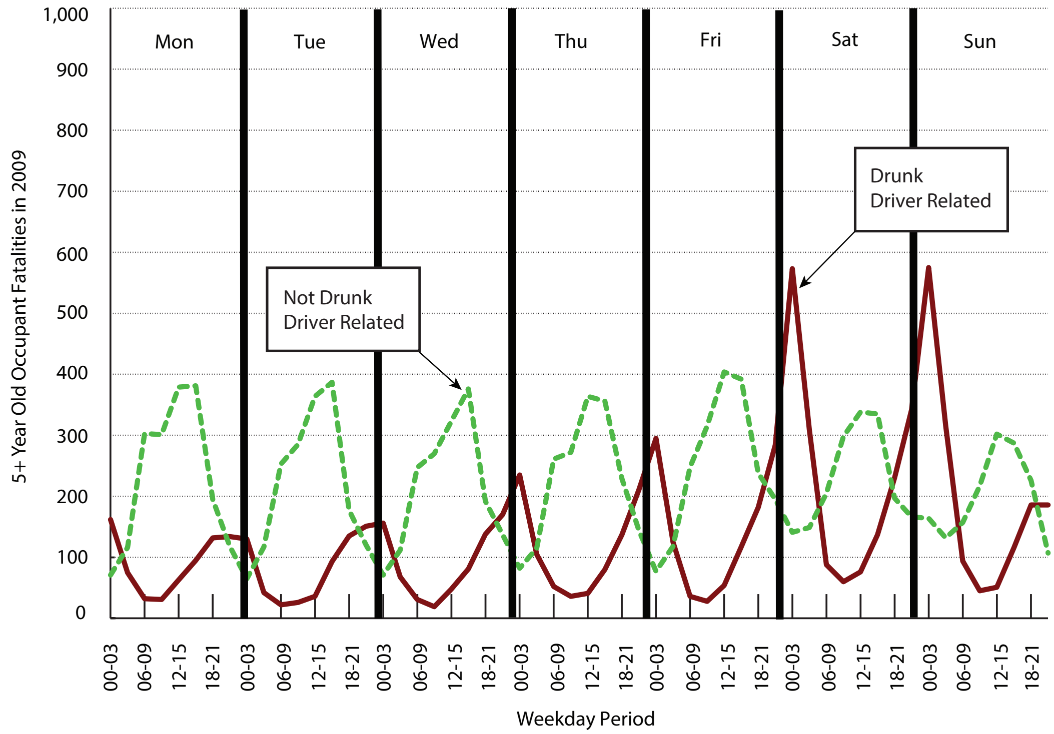
To facilitate statistical analysis of the circadian risk data in Figure 13, each *day* was again defined to begin and end at noon rather than midnight, and *period of day* was again defined as the sequence of eight 3-hour periods in such a day. The drunk-driver- and nondrunk-driver-related risk data in Figure 13 were analyzed, respectively, via separate hierarchical quasi-likelihood generalized linear regression models relating the natural log of fatality risk to the covariates: day (linear and quadratic components coded via orthogonal polynomials), period of day (linear and quadratic components coded via orthogonal polynomials), and period of day by day (set of pairwise products of the day and period of day codes). Drunk-driver-related occupant fatality risk increased through the week as revealed by a linear day effect (p=.015), was circadian as confirmed by a quadratic period of day effect (p<.0001), and shifted later in the day as the week progressed as revealed by a linear period of day by linear day interaction (p=.035). Nondrunk-driver-related occupant fatality risk was circadian as confirmed by a quadratic period of day effect (p=.034), with no other significant effects.

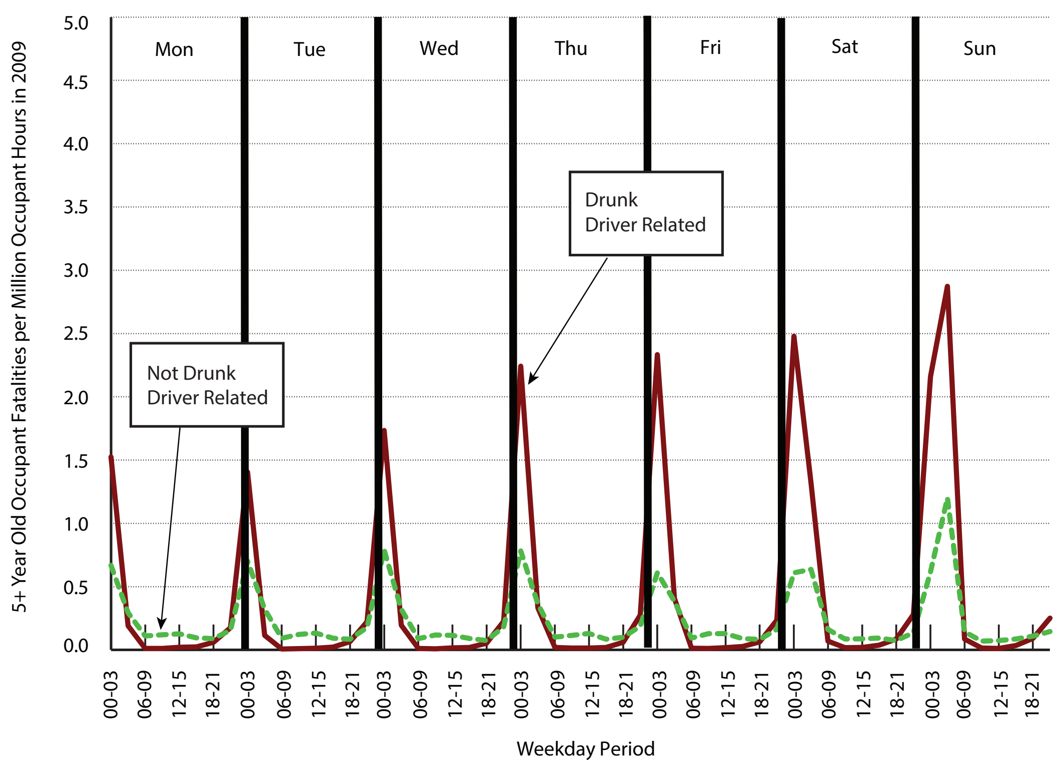
The risk data in Figure 13 must be interpreted cautiously, because drunk-driver-related occupant fatality risk is also strongly associated with age and sex (e.g., young male occupants exhibit the greatest risk by far). The purpose of Figure 13 is to show that occupant fatality risk remains strongly circadian with drunk-driver-related fatalities removed. Although many factors are correlated with period of day and week, such as darkness, traffic volume, travel purpose, and so on, the remarkable circadian periodicity of occupant fatality risk—across demographic age-sex populations, days of the week, and drunk- and nondrunk-driver-related fatal crashes—suggests a drowsiness component acting alone, and sometimes synergistically with alcohol, to impair the judgment and performance of motor vehicle occupants. Much evidence in the literature, some of which is discussed below, supports a drowsiness explanation of the circadian occupant risk data reported herein.

Conclusions

While previous research has demonstrated age, sex, day of week, and time of day effects on motor vehicle crashes and crash risk based on trips, vehicle miles, or occasionally occupant miles traveled [e.g., 16, 19, 23–25, 30, 41, 46], the present study appears to be the first to define and quantify motor vehicle occupant fatality risk in terms of occupant hours of travel. Results demonstrated the robust circadian periodicity of motor vehicle occupant fatality risk across age-sex populations, days of the week, and drunk- and nondrunk-driver-related fatal crashes, with much higher risk during late-evening and early-morning hours every day of the week and the greatest risk during the Friday–Saturday and Saturday–Sunday late evening-early morning hours

Figure 13: Occupant Fatalities and Fatality Risk by Drunk-Driver Relatedness and Period of Week in 2009





SOURCES: National Highway Traffic Safety Administration (FARS); Federal Highway Administration, National Household Travel Survey; and Bureau of Transportation Statistics, 2012.

when more fatalities and higher fatality risk are associated with drunk-driver-related crashes. But these circadian trends also interact with age and sex, with young male occupants exhibiting the most fatalities and fatality risk and the difference in risk between male and female occupants diminishing with age.

The circadian periodicity of motor vehicle occupant fatality risk across age-sex populations, days of the week, and drunk- and nondrunk-driver-related fatal crashes suggests a drowsiness component acting alone, and sometimes synergistically with alcohol, to impair the judgment and performance of motor vehicle occupants. A drowsiness explanation is supported by considerable evidence in the literature, including a recent study estimating that 16.5 percent of fatal crashes in the United States from 2000 to 2008 involved a drowsy driver [60]. Both homeostatic and circadian rhythm (biological clock) processes influence the neurobiological need to sleep, and the longer the time awake, the greater the pressure to sleep and difficulty resisting it [61]. Falling asleep at the wheel, and departing the roadway at high speed with no sign of braking, is the most obvious drowsiness-related crash type, but not the only or even most prevalent one [50]. Drowsiness causes a variety of impairments of sensorimotor and cognitive processes essential to safe driving, e.g., slower reaction times to stimuli, reduced vigilance in attention-demanding tasks, and deficits in information processing such as memory performance and processing and integrating information [61–62].

Furthermore, evidence that sleep deprivation depletes self-regulatory resources necessary to sustain executive processes related to self-control, hostility, and impulse inhibition, thereby increasing deviance from societal norms [63], may explain some deviant roadway activities (excessive acceleration, speeding, drunk driving, etc.) during late night–early morning periods, when many motor vehicle occupants have been awake hours into their usual sleep periods and already carry a debilitating sleep debt [64, p. 70] accumulated over prior days of insufficient sleep.

The circadian periodicity of motor vehicle occupant fatality risk has implications for occupant injury and fatality risk reduction efforts. First, these results identify regions of motor vehicle occupant exposure space where occupant fatality risk is highly concentrated and where mitigation resources must be focused to effectively reduce this risk.

Second, it is misleading for public health communications to describe motor vehicle occupant risk as if it were uniform over time and other factors, e.g., “An average of 92 people died each day in motor vehicle crashes in 2012—one every 16 minutes.” [1, p. 1] This widely prevalent miscommunication of risk information ignores the strong association of motor vehicle occupant fatalities and risk with age, sex, period of week, and other factors, and reinforces the fatalistic view that fatalities are random and there is little we can do to predict or prevent them.

Third, the results suggest that providing accurate risk information to the public, e.g., in driver education and advertising, could reduce risk by encouraging people, especially young high-risk populations, to monitor and control exposure to high risk regimes of motor vehicle travel. Public health messaging and education is needed to accurately convey the distribution of motor vehicle occupant risk across age, sex, and period of week, and to communicate mitigation strategies, e.g., minimizing high risk travel, getting sufficient sleep, and being vigilant for and appropriately responsive to impulsive or otherwise deviant driver behaviors during such travel—whether in one’s own vehicle or another’s.

Fourth, these results suggest the possibility of an inexpensive onboard risk monitoring device, using strong indicators of motor vehicle occupant risk (such as period of week and other reliable predictors) to indicate risk to drivers and passengers and facilitate their ability to monitor and control exposure to the highest risk regimes of motor vehicle travel. But such instrumentation must be carefully researched and developed before implementation to prevent undesirable side effects such as driver distraction or risk-seeking behaviors.

Finally, these results implicate sleep deprivation and drowsiness as critical underlying components of motor vehicle occupant fatality risk that need to be more widely recognized and studied, better communicated to the public and policy makers, and systematically addressed via all feasible means.

End Note

The views in this paper are those of the author and do not necessarily represent the official views of the U.S. Department of Transportation or any other agency or staff.

References

1. National Highway Traffic Safety Administration (NHTSA), U.S. Department of Transportation. *Traffic Safety Facts 2012 Data*. Washington, DC; May, 2014 (Revised). Downloaded on April 23, 2015 at: http://www-nrd.nhtsa.dot.gov/Pubs/812016.pdf.

2. National Highway Traffic Safety Administration (NHTSA). U.S. Department of Transportation. *Traffic Safety Facts 2012*. DOT HS 812 032. Washington, DC; 2014. Downloaded on May 22, 2015 at: http://www-nrd.nhtsa.dot.gov/Pubs/812032.pdf.

3. National Highway Traffic Safety Administration (NHTSA). U.S. Department of Transportation. *2013 Motor Vehicle Crashes: Overview*. DOT HS 812 101. Washington, DC; 2014. Downloaded on May 22, 2015 at: http://www-nrd.nhtsa.dot.gov/Pubs/812101.pdf.

4. Kochanek KD, Xu J, Murphy SL, Miniño AM, Kung H-C. Deaths: Preliminary Data for 2009. *National Vital Statis-*

tics Reports 59(4), National Center for Health Statistics, Washington, DC; 2011.

5. Arnett JJ. Developmental sources of crash risk in young drivers. *Injury Prevention* 8 (Supplement II):ii17–ii23; 2002.

6. Arnett JJ, Offer D, Fine MA. Reckless driving in adolescence: ‘State” and “trait” factors. *Accident Analysis and Prevention* 29:57–63; 1997.

7. Austin RA, Faigin BM. Effect of vehicle and crash factors on older occupants. *Journal of Safety Research* 34:441–452; 2003.

8. Chen L-H, Baker SP, Braver ER, Li G. Carrying passengers as a risk factor for crashes fatal to 16- and 17-year-old drivers. *Journal of the American Medical Association* 283(12):1578–1582; 2000.

9. Chipman ML, MacGregor CG, Smiley AM, Lee-Gosselin M. The role of exposure in comparisons of crash risk among different drivers and driving environments. *Accident Analysis and Prevention* 25:207–211; 1993.

10. Clarke DD, Ward P, Bartle C, Truman W. Young driver accidents in the UK: the influence of age, experience, and time of day. *Accident Analysis and Prevention* 38: 871–878; 2006.

11. Doherty ST, Andrey JC, MacGregor, C. The situational risks of young drivers: the influence of passengers, time of day and day of week on accident rates. *Accident Analysis and Prevention* 30:45–52; 1998.

12. Dubinsky RM, Stein AC, Lyons K. Practice Parameter: Risk of Driving and Alzheimer’s Disease (An Evidence-Based Review). *Report of the Quality Standards Subcommittee of the American Academy of Neurology*. St. Paul, MN; 2000.

13. Elvik R. Laws of accident causation. *Accident Analysis and Prevention* 38:742–747; 2006.

14. Engström I, Gregersen NP, Granström K, Nyberg A. Young drivers–Reduced crash risk with passengers in the vehicle. *Accident Analysis and Prevention* 40:341–348; 2008.

15. Farrow JA. Young driver risk taking: A description of dangerous driving situations among 16- to 19-year-old drivers. *International Journal of Addiction* 22(12):1255–1267; 1987.

16. Folkard S. Black times: Temporal determinants of transport safety. *Accident Analysis and Prevention* 29:417–430; 1997.

17. Fuller R. The psychology of the young driver. In Fuller R, Santos JA. *Human Factors for Highway Engineers*. New York: Pergamon; 2002.

18. Hing JYC, Stamatiadis N, Aultman-Hall L. Evaluating the impact of passengers on the safety of older drivers. *Journal of Safety Research* 34:343–351; 2003.

19. Horne J, Reyner L. Vehicle accidents related to sleep: a review. *Occupational and Environmental Medicine* 56:289–294; 1999.

20. Keall MD, Frith WJ. Older driver crash rates in relation to type and quantity of travel. *Traffic Injury Prevention* 5:26–36; 2004.

21. Kocher KE, Dellinger AM. Nonfatal Injuries among Older Adults Treated in Hospital Emergency Departments–United States, 2001. *MMWR Online* 52(42); 2003.

22. Laapotti S, Keskinen E, Hatakka M, Katila A. Novice drivers’ accidents and violations–a failure on higher or lower hierarchical levels of driving behaviour. *Accident Analysis and Prevention* 33:759–769; 2001.

23. Lenne MG, Triggs TJ, Redman JR. Time of day variations in driving performance. *Accident Analysis and Prevention* 29:431–437; 1997.

24. Lenne MG, Triggs TJ, Redman JR. Interactive effects of sleep deprivation, time of day, and driving experience on a driving task. *Sleep* 1998; 21(1):38–44.

25. Lyznicki JM, Doege TC, Davis RM, Williams MA. Sleepiness, driving, and motor vehicle crashes. *Journal of the American Medical Association* 279:1908–1913; 1998.

26. Mayhew DR, Simpson HM. The safety value of driver education and training. *Injury Prevention* 8 (Supplement II):ii3–ii8; 2002.

27. Mayhew DR, Simpson HM, Pak A. Changes in collision rates among novice drivers during the first months of driving. *Accident Analysis and Prevention* 35:683–691; 2003.

28. McCartt AT, Northrup VS. Factors related to seat belt use among fatally injured teenage drivers. *Journal of Safety Research* 35:29–38; 2004.

29. McKnight AJ, McKnight AS. Young novice drivers: careless or clueless? *Accident Analysis and Prevention* 35, 921–925; 2003.

30. National Center for Statistics and Analysis, National Highway Traffic Safety Administration, U.S. Department of Transportation. *Exposure to Accidents: Who? When?* A study using data from the National accident sampling system and the 1977 nationwide personal transportation study. Washington, DC; 1982.

31. Patten CJD, Kirchner A, Ostlund J, Nilsson L, Svenson O. Driver experience and cognitive workload in different traffic environments. *Accident Analysis and Prevention* 38:887–894; 2006.

32. Preusser DF, Ferguson SA, Williams AF. The effect of teenage passengers on the fatal crash risk of teenage drivers. *Accident Analysis and Prevention* 30(2):217–222; 1998.

33. Reyna VF, Farley F. Is the teen brain too rational? *Scientific American Mind* Dec 2006–Jan 2007:59–65; 2006.

34. Schwebel DC, Severson J, Ball KK, Rizzo M. Individual difference factors in risky driving: The roles of anger/hostility, conscientiousness, and sensation-seeking. *Accident Analysis and Prevention* 38:801–810; 2006.

35. Shinar D, Compton R. Aggressive driving: an observational study of driver, vehicle, and situational variables. *Accident Analysis and Prevention* 36:429–437; 2004.

36. Simons-Morton B. Reducing young driver crash risk. *Injury Prevention*. Downloaded from http://injuryprevention.bmj.com/ on April 29, 2015; 2002.

37. Simons-Morton, B., Lerner, N., Singer, J., 2005. The observed effects of teenage passengers on the risky driving behavior of teenage drivers. *Accident Analysis and Prevention* 37, 973–982; 2005.

38. Stewart DE, Sanderson RW. The measurement of risk on Canada's roads and highways. In Yagar S (Ed.) *Transportation Risk Assessment*. University of Waterloo Press, 1–21; 1984.

39. Vollrath M, Meilinger T, Krüger H-P. How the presence of passengers influences the risk of a collision with another vehicle. *Accident Analysis and Prevention* 34:649–654; 2002.

40. White WT. Just how unsafe are young drivers? In *Road Traffic Safety Seminar*, Road Traffic Safety Council. Wellington, New Zealand 374–410; 1988.

41. Williams AF. Nighttime driving and fatal crash involvement of teenagers. *Accident Analysis and Prevention* 17:1–5; 1985.

42. Williams AF, Shabanova VI. Responsibility of drivers, by age and sex, for motor-vehicle crash deaths. *Journal of Safety Research* 34:527–531; 2003.

43. Zador PL, Krawchuk SA, Voas RB. Alcohol-related relative risk of driver fatalities and driver involvement in fatal crashes in relation to driver age and sex: an update using 1996 data. *Journal of Studies on Alcohol* May, 387–395; 2000.

44. Morris CC. Generalized linear regression analysis of association of universal helmet laws with motorcyclist fatality rates. *Accident Analysis and Prevention* 2006; 38:142–147.

45. Morris CC. Quasi-likelihood generalized linear regression analysis of fatality risk data. In Slaboda BW (Ed.), *Transportation Statistics*. Ft. Lauderdale, FL: Ross; 2009.

46. Schwing RC, Kamerud DB. The distribution of risks: Vehicle occupant fatalities and time of the week. *Risk Analysis* 8(1):127–133; 1988.

47. Wolfe AC. The concept of exposure to the risk of a road traffic accident and an overview of exposure data collection methods. *Accident Analysis and Prevention* 14, 337–340; 1982.

48. Haight FA. Risk, especially risk of traffic accident. *Accident Analysis and Prevention* 18:359–366; 1986.

49. Hakkert AS, Braimaister L. *The uses of exposure and risk in road safety studies*. SWOV Institute for Road Safety Research. Leidschendam, The Netherlands; 2002.

50. Pack, AI, Pack, AM, Rodgman, E, Cucchiara, A, Dinges, DF, Schwab, CW. Characteristics of crashes attributed to the driver having fallen asleep. *Accident Analysis and Prevention* 1995; 27:769–775.

51. Selvin S. *Statistical Analysis of Epidemiologic Data*. New York: Oxford University Press; 1996.

52. Morris CC. *Concept and measurement of transportation fatality risk*. Draft technical report. Bureau of Transportation Statistics. U.S. Department of Transportation. Washington, DC; 2015.

53. Aarts L, van Schagen I. Driving speed and the risk of road crashes: a review. *Accident Analysis and Prevention* 2006; 38:215–224.

54. Pipeline and Hazardous Materials Administration (PHMSA). *A Comparison of Risk*. U.S. Department of Transportation. Washington, DC; 2004. Downloaded on April 7, 2015 at: http://www.phmsa.dot.gov/portal/site/PHMSA/menuitem.6f23687cf7b00b0f22e4c6962d9c8789/?vgnextoid=8524adbb3c60d110VgnVCM1000009ed07898RCRD&vgnextchannel=4f347fd9b896b110VgnVCM1000009ed07898RCRD&vgnextfmt=print.

55. Collia DV, Sharp J, Giesbrecht L. The 2001 national household travel survey: A look into the travel patterns of older Americans. *Journal of Safety Research* 34:461–470; 2003.

56. Federal Highway Traffic Safety Administration (FHWA), U.S. Department of Transportation. *2009 National Household Travel Survey User's Guide* Feb 2011 Version 1. Washington, DC; 2011.

57. Centers for Disease Control. Downloaded from the Centers for Disease Control website at http://wonder.cdc.gov/Bridged-Race-v2009.HTML on May 17, 2012.

58. National Highway Traffic Safety Administration (NHTSA). *Fatality Analysis Reporting System General Estimates System 2009 Data Summary* 2011. DOT HS 811 401. U.S. Department of Transportation.

59. Centers for Disease Control. Downloaded from the Centers for Disease Control (WISQORS) website at http://www.cdc.gov/injury/wisqars/nonfatal.html on May 17, 2012.

60. Tefft BC. Prevalence of motor vehicle crashes involving drowsy drivers, United States, 1999–2008. *Accident Analysis and Prevention* 45:180–186; 2012.

61. National Center on Sleep Disorders Research of the National Heart, Lung, and Blood Institute, National Institutes of Health and National Highway Traffic Safety Administration, U.S. Department of Transportation, 1998. DOT HS 808 707. *Drowsy driving and automobile crashes*. Washington, DC.

62. Williamson A, Lombardi DA, Folkard S, Stutts J, Courtney TK, Connor JL. The link between fatigue and safety. *Accident Analysis and Prevention* 2011; 43:498–51.

63. Christian MS, Ellis APJ. Examining the effects of sleep deprivation on workplace deviance: A self-regulatory perspective. *Academy of Management Journal* 54:913–934; 2011.

64. Smolensy M, Lamberg L. *The Body Clock Guide to Better Health*. New York: Henry Hold and Company; 2000.