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MALE/FEMALE DRIVER CHARACTERISTICS AND ACCIDENT RISK: SOME NEW EVIDENCE

FRED L. MANNERING

Department of Civil Engineering, 121 More Hall, FX-10, University of Washington, Seattle, WA 98195, U.S.A.

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Abstract—Due to the high correlation that generally exists among driver characteristics, as well as the overall complexity of the factors involved, the role that gender plays in the relationship between driver characteristics and accident risk has been difficult to quantify using traditional statistical approaches. This paper attempts to provide some new insight by using hazard functions and a sample of University of Washington drivers. The subsequent empirical analysis uncovers important differences in the relationship between male and female driver characteristics and their respective accident risk.

INTRODUCTION

Understanding and quantifying the relationship between driver characteristics and accident risk has long been a high priority of accident-related research. And with good reason, since the accurate statistical modeling of this relationship has the potential to substantially improve the equity of insurance premiums (particularly by gender and age) and, more important, lead to more effective accident prevention policies. However, uncovering the relationship between driver characteristics and accident risk, and differences by gender, is a formidable task due, in large part, to the often confounding relationships that exist among specific driver characteristics. A classic example of this is the relationship between a driver's age and driving experience. That is, while it is known that younger drivers have high accident rates, the very high correlation between age and driving experience makes it exceedingly difficult to statistically separate the effect of the aggressive risk-taking behavior generally assumed to be associated with younger drivers from the simple lack of driving experience.

Numerous research studies have made attempts to unravel the complex relationship between driver characteristics and accident risk and thereby provide some evidence on possible gender differences. The majority of these studies begin by focusing on driver characteristics that are theoretically appealing but are conceptual in nature and difficult to measure. Such characteristics include: (i) drivers' risk-taking behavior, (ii) driving experience and the quality of that experience, and (iii) exposure to risk of an accident. The task then becomes one of using readily measurable driver characteristics to define these important conceptual characteristics. For example, drivers' risk-taking behavior is often defined in terms of drivers' age and gender, type and age of car driven, as well as drivers' accident, moving violation, and alcohol/drug consumption history. Driving experience and the quality of that experience can be defined using the number of years driven, total accumulated miles driven, and information relating to the proportion of driving undertaken on different road types (e.g. freeways, arterials, rural) and conditions (e.g. rain, snow). Another key concern here is manner in which drivers learn from their experience. Two drivers with identical experiences (and all other factors equal) may have substantially different accident risks due to their having learned at different rates. These learning rates may be a function of measurable characteristics such as age, gender, and so on. Finally, exposure to accident risk (which ultimately contributes to driving experience) has been represented by the amount of driving (e.g. annual accumulated mileage), and again the proportion of driving by road types and conditions. From a practical point of view, the use of measurable characteristics to represent underlying conceptual characteristics can be problematic, since measurable characteristics often influence more than one of the conceptual characteristics (e.g. driving on different road types and under different conditions affects both driving experience and accident risk exposure). This is further compounded by the high correlation that exists among various measurable driver characteristics, as previously mentioned (e.g. the high correlation between age, driving experience, and exposure to accident risk). As a result of these complexities, it is virtually impossible to fully quantify the true cause and effect relationship between driver characteristics (both conceptual and measurable) and accident risk and to determine differences by gender. However, past research has provided important insights into this relationship, and these insights have brought the profession closer to a fuller understanding of the underlying driver characteristic/accident risk relationship.

Arguably the most important work in this field has sought to relate a single measurable driver characteristic (driver's age) with accident risk. Important summaries of the research conducted on the relationship between age and accident risk include those of Jonah (1986), Cameron (1982), and Valentine, Williams, and Young (1978). Basically, research efforts in this area have attempted to explain the higher accident rates of younger drivers (relative to older drivers) on the grounds of their (i) tendency to drive more and thus have a higher exposure (Stewart and Sanderson 1984; Lee, Glover, and Eavy 1980), (ii) inexperience (Mayhew and Simpson 1990; Michiels and Schneider 1984; Brown 1982; Pelz and Schuman 1971), (iii) overconfidence in their own driving skills and abilities (Groeger and Brown 1989; McCormick, Walkey, and Green 1986), and (iv) tendency to speed and tailgate (Evans and Wasielewski 1983; Wasielewski 1984). All of these studies have had to struggle with the high correlation among measurable driver characteristics and the fact that age itself is really being used as a surrogate for drivers' risk-taking behavior. As a result, their findings may not have been as conclusive as readers would like, but this is to be expected given the nature of the problem. Their contribution has been one of adding incrementally to our knowledge base.

The objective of this paper is to collect a sample of male and female drivers and to apply a hazard function approach to isolate key differences in their respective driver characteristic/accident risk relationship. The hazard function approach is a departure from traditional statistical modeling methods used in the accident analysis field in that the focus is on conditional probabilities (i.e. the probability of accident occurrence conditioned on the time since the individual's last accident involvement). It is hoped that such an approach can provide some additional insight as to why automobile insurance companies may or may not be justified in offering different insurance rates on the basis of gender. That is, is gender a key determinant of accident risk or, is it merely reflecting a deeper causality that is being masked by confounding relationships that exist among driver characteristics?

The paper begins by presenting the details of the methodological approach. Next, the results of a recently conducted survey of accident involvement are presented, and this survey is used as a basis for conducting the hazard function statistical analysis. Finally, the findings are summarized, and directions for future work in this area are discussed.

METHODOLOGICAL APPROACH

A promising way of studying the driver characteristic/accident risk relationship is to view the process of accident occurrence as an analysis of survival. Survival, in this case, being the length of time (duration) over which a driver does not have an accident. The hazard function approach to survival analysis has long been used as a means of determining causality in duration data. For instance, engineering and biomedical fields have used the hazard function approach to study machine failures and patient deaths. Economists have used the approach to study the duration of individuals' unemployment spells. In the accident analysis arena, the application of the approach is rather new. Jovanis and Chang (1989) have applied hazard functions to study accident likelihood on individual trips and later formulated a general procedure for applying the approach to the study of accident occurrence (Chang and Jovanis 1990).

In this paper, the application of the hazard function approach is achieved by focusing on the time (duration) until accident occurrence and then statistically determining the effect that driver characteristics have on this time. To illustrate the organization of such data, consider the accident records of the four drivers shown in Fig. 1. As the figure indicates, these four drivers produce ten until-accident durations, four of which (t_3, t_4, t_8, t_{10}) are censored (i.e. a survey conducted in 1990 would be unable to determine the end of these duration periods). The hazard function approach to modeling until-accident duration considers the probability of an accident (i.e. ending the duration period) conditioned on the driver's not having an accident up to a specified time. Formally, let $F(t)$ be the cumulative distribution function of until-accident durations (i.e. giving the probability of having an accident before some transpired time, t), then

$$F(t) = \Pr[T < t] \qquad (1)$$

where Pr denotes probability, T is a random time variable, and t is some specified time. The corresponding density function (the first derivative of the cumulative distribution function with respect to time), $f(t)$ is

$$f(t) = dF(t)/dt \qquad (2)$$

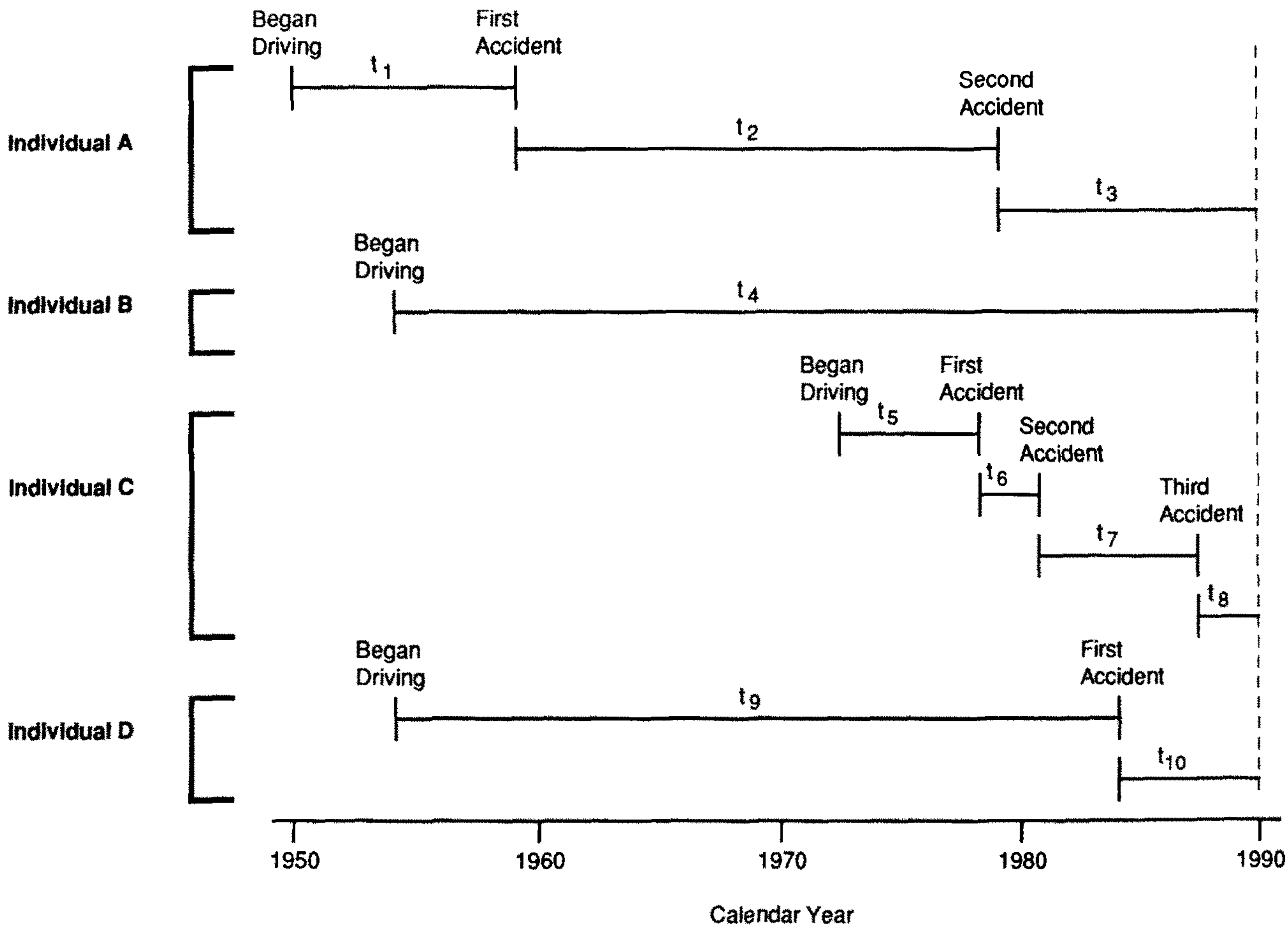

Fig. 1. Examples of individuals' duration of time until an accident

and the hazard function is

$$h(t) = f(t)/[1 - F(t)] \tag{3}$$

where the hazard function $h(t)$ is the conditional probability that an accident will occur between time t and $t + dt$, given that no accident has occurred until time t. Alternatively stated, $h(t)$ is roughly the rate at which accidents occur (i.e. durations are ending) at time t, given that no accident has occurred until time t.

In considering the time until accident occurrence, the first derivative of the hazard function with respect to time, $dh(t)/dt$, has important implications. If the value of this derivative is greater than zero at some time t, the hazard is increasing in duration, indicating that the probability of an accident increases the longer one goes without having an accident. If $dh(t)/dt$ is less than zero, a decreasing hazard exists and the probability of an accident decreases the longer one goes without having an accident. Finally, if $dh(t)/dt$ is equal to zero, the probability of accident occurrence is independent of the length of time the driver has gone without having an accident.

To apply the hazard function approach, it is necessary to select an appropriate probability distribution for the duration of time until accident occurrence. An alternative is to formulate the problem as a semiparametric model in which a distributional assumption concerning duration is not required. See Cox and Oates (1984) for details concerning such an approach. The Weibull distribution is an obvious choice with its relatively simple hazard. The occurrence of an accident (which ends until-accident duration) is typically induced by any one of a number of rare events such as unusual traffic conditions, boredom, lack of concentration, unusually poor visibility, falling asleep at the wheel, and so on. Therefore, the time until accident occurrence depends on the shortest time to the occurrence of one of these rare random events (i.e. the distribution of the smallest extreme), which in turn provides a theoretical justification for using the extreme-value based Weibull distribution.

The two parameter Weibull ($\gamma > 0$ and $\rho > 0$) has

$$F(t) = 1 - \exp[-(\gamma t)^{\rho}] \tag{4}$$

$$f(t) = \gamma\rho(\gamma t)^{\rho-1} \exp[-(\gamma t)^{\rho}] \tag{5}$$

with hazard,

$$h(t) = \gamma\rho(\gamma t)^{\rho-1} \tag{6}$$

In this case the hazard is increasing in duration if $\rho >$ 0, decreasing in duration if $\rho < 1$, and independent of duration if $\rho = 1$.

To consider the effects that covariates (in our case, driver characteristics) have on the duration of time until accident occurrence, a generalization of Eqn 6 is required. A common generalization is the proportional hazards model, which offers flexibility in choosing the underlying distributional forms of the hazard and produces parameter estimates that can be readily interpreted (Kalbfeisch and Prentice 1980). An alternative to the proportional hazards model is the accelerated lifetime model (see Mannering and Hamed, 1990 for an application of this model). It can be shown that with the selection of the Weibull distribution, proportional hazards, and accelerated lifetime model assumptions are satisfied (Fleming and Harrington 1990). The premise of the proportional hazards model is that the covariates act multiplicatively on the hazard function. The typical form of this model is

$$h(t|\mathbf{X}) = h_0(t) \exp(-\beta\mathbf{X}) \tag{7}$$

where $h(t|\mathbf{X})$ is the hazard function conditioned on covariate vector $\mathbf{X}$, $h_0(t)$ is the baseline hazard (the hazard for an individual for whom the vector $\mathbf{X}$ is zero) and β is a vector of estimable coefficients. Note that this model assumes that the covariates act multiplicatively on the baseline hazard function, such that an increase of d in covariate x_1, for example, will result in a multiplicative increase in the hazard by a factor of $\exp(-\beta_1 d)$, regardless of the initial value of x_1 (i.e. $h(t|\mathbf{X}) = h_0(t)\exp(-\beta\mathbf{X})\exp(\beta_1 d)$).

This form also implies that an increase in any one covariate is dependent on the values of all other covariates and thus explicitly recognizes the complex interaction between covariates and accident risk. (See Chang and Jovanis 1990 for a further discussion of these points.)

Given the selection of the Weibull distribution for $h_0(t)$ (i.e. the distribution of the times until an accident), the following proportional hazards model results,

$$h(t|\mathbf{X}) = \gamma\rho(\gamma\rho)^{\rho-1} \exp(-\beta\mathbf{X}) \tag{8}$$

This model is readily estimable by standard maximum likelihood methods. The presence of censored data (see Fig. 1) can be accounted for with standard modifications to the likelihood function. See Kalbfleisch and Prentice (1980) for further details.

DATA DESCRIPTION

To apply the proportional hazards model approach to study the relationship between driver characteristics and accident risk, a survey was conducted in May 1990. The survey collected the complete accident and moving violation history of drivers since their initial licensing, along with a history of key socioeconomic information. (An accident was defined as those collisions resulting in more than one hundred dollars property damage, regardless of fault.) The respondents were chosen from the student body and staff of the University of Washington, Seattle. The survey was conducted as a stratified random sample. The primary stratification was by gender, with males being oversampled (70% to 30%) due to a priori expectations of their having higher accident rates, particularly among young drivers. The sample was limited to University of Washington senior undergraduates (thus ensuring some level of experience and/or maturity), graduate students, faculty, and staff. The data were also stratified by senior undergraduates, graduates, faculty, and staff to ensure that the survey response rates were similar across these strata. No significant difference in response rates (or in incorrectly filled-out survey forms) was detected and the sampling rates within these strata were in exact proportion to their overall population within the university community. Sampling was undertaken by random selection within strata using university personnel sources.

A total of 200 surveys were distributed (140 male, 60 female) and 126 males and 53 females eventually responded. Incorrectly filled-out forms reduced the sample to 114 male and 46 female. The summary statistics of this 160 driver sample are presented in Table 1. Overall, the values presented in this table are fairly consistent with expectations. Of particular interest is the duration until accident occurrence, which is used as the dependent variable in the estimation of the proportional hazards model. (Note that due to the fact that censored values are excluded, the values of this variable, as shown in Table 1, are "biased" downward.) Since individuals in our survey averaged having roughly one accident, the sample produced 222 duration values for males, 114 of which are censored, and 101 for females, 46 of which are censored. Note that each individual in the sample will produce a censored observation since it is highly unlikely that he/she will have had an accident on the

Table 1. Summary statistics (averages unless otherwise noted)

Variable	Male	Female
Age (years)	31.64	32.02
Annual household income (dollars)	28,995	30,455
Percent married	26.32	30.44
Percent wearing corrective lenses	54.39	65.22
Number of household vehicles	1.52	1.76
Number of accidents	0.99	1.07
Percent ever having an accident	60.53	56.52
Number of miles driven per year	9,974	9,239
Number of years past 16 years of age, began driving	3.22	3.15
Percent that started to drive at 16 years of age	58.56	52.48
Total accumulated years of driving experience	11.09	11.61
Total accumulated miles of driving experience	112,509	100,174
Number of moving violations	1.03	0.96
Percent ever having a moving violation	44.73	41.30
Duration until accident occurrence for uncensored observations (years)	4.09	4.44
Number of respondents	114	46

Table 2. Duration until accident occurrence for male and female drivers (t-statistics in parentheses)

	Estimated coefficient	
Variable	Male	Female
Constant	2.394	2.597
	(7.61)	(6.75)
Number of miles driven per year (in thousands)	−0.058	−0.056
	(−2.65)	(−2.71)
Married indicator (1 if driver was married, 0 otherwise)	0.346	1.691
	(1.22)	(3.35)
Annual household income (in thousands of dollars)	0.0128	0.0135
	(2.48)	(1.55)
Moving violation indicator (1 if driver had a previous moving violation, 0 otherwise)	−0.727	—
	(−2.99)	
Log of the total accumulated miles of driving experience (in thousands of miles)	0.380	—
	(2.96)	
Accident indicator (1 if driver had a previous accident, 0 otherwise)	—	−0.530
		(−1.61)
Number of years past 16 years of age, began driving	—	−0.593
		(−2.46)
Log of the total accumulated years of driving experience	—	0.318
		(1.61)
Duration parameter	0.809	1.09
	(8.80)	(6.99)
Log-likelihood at convergence	−277.88	−110.11
Number of observations	222	101

exact day that the survey was conducted. Thus some time will have passed between the occurrence of the last accident and the time of survey completion (see Fig. 1 for an illustration of censoring).

Finally, it is important to mention that the collection of self-reported data (such was done in this survey), while easily obtained, presents a number of potential problems. These include the possibility that individuals may not accurately recall their past accident histories or that they may deliberately underreport accident involvement. The solution to this would be to connect the self-reported data to actual accident record data. Unfortunately, budget limitations and the relatively large number of out-of-state respondents in the University of Washington sample prevented the use of actual accident record data.

ESTIMATION RESULTS

The estimation results of the Weibull proportional hazards model of the duration of time until accident occurrence are presented in Table 2, for both male drivers and female drivers.

The values of the characteristics (e.g. income, age and so on) used in the estimation of the models present in Table 2, are those values, as they existed, at the beginning of the duration spell (i.e. either when the individual was first licensed or immediately after accident occurrence). Although it is possible to include time-varying covariates in the hazard formulation, it is rarely done due to the complexity of the likelihood function and the fact that the coefficients of such variates are difficult to interpret (see Kalbfleisch and Prentice 1984). The estimated coefficients presented in Table 2 are those comprising the β vector as shown in Eqn 8.

The difference between the male/female driver characteristic/accident risk relationship (as implied by the duration of time until accident occurrence) is significant at over the 99% confidence level, as indicated by the chi-squared statistic produced by a likelihood ratio test, which compares the convergence log-likelihoods of a single combined male/female model with those from the separate male/female models shown in Table 2. The observed gender differences are quite provocative in terms of what they imply concerning the driver characteristic/accident risk relationship. This is discussed in detail below.

A number of driver characteristics (covariates) are common to both male and female hazard models. The first of these is the number of miles driven per year, which is one of the classic measures of accident exposure. In both male and female models, the coefficient is negative, as expected, indicating that an increase in annual mileage increases the hazard (i.e. increases the likelihood of accident occurrence, see Eqn 8) and thus decreases the duration of time until accident occurrence. This variable also has roughly the same statistical significance (as indicated by t-statistics) and magnitude in both models. This is further borne out by looking at the implied elasticities presented in Table 3. Elasticities are used here to measure the effect that a change in covariates have on the duration until accident occurrence. This notion of elasticity, which is used extensively in economics, is expressed mathematically as $(\partial D/\partial k)(k/D)$, where D is the duration until accident occurrence and k is a selected covariate (e.g. miles driven per year). Elasticity calculations are a critical measure of how sensitive the dependent variable (in this case the duration until accident occurrence) is to changes in specific covariates. For example, the elasticities in Table 3 can be roughly interpreted as the effect of a one percent increase in annual mileage is to decrease the time until accident occurrence by 0.595% for males and 0.504% for females. Since the absolute values of these elasticities are less than one, the time until accident occurrence is inelastic with respect to the number of miles driven per year.

The marital status of the driver was also found to be a factor in both male and female duration models, but more so in the female model both statistically and in terms of coefficient magnitude. The coefficients in both models are positive, indicating that married drivers have longer durations until accident occurrence (i.e. lower accident risk). This variable could be a measure of the driver's risk-taking behavior, although being married could also change driving patterns (e.g. joint trips) and thus exposure to the risk of an accident. By formulating the problem as the time until (for beginning drivers) or between accidents (for seasoned drivers), it is not possible to account for specific risk components such as roadway types, environmental conditions, and so on. For an example of how such risk components can be used in the context of hazard functions see Jovanis and Chang (1989).

The final characteristic common to both male and female models is income. In both models the effect of income is roughly the same (see elasticities in Table 3) with the positive sign indicating that drivers from higher income households have longer durations until an accident (lower accident risk) than their lower income counterparts. Three possible explanations for this can be proposed. First, income may be highly correlated with maturity and thus associated with risk-taking behavior. Certainly, income is correlated with age (a commonly used measure of risk-taking behavior as previously discussed), and the absence of age is one of the most noteworthy features of the male and female duration models, particularly in light of the previous research relating age with accident risk (Jonah 1986). Attempts to include drivers' age in these models proved fruitless, as the resulting age coefficients were not statistically different from zero (t-statistics less than 0.3). Thus it appears that the correlation between age and accident occurrence is being explained by other variables that are accounting for risk-taking behavior, as well as male/female differences.

Table 3. Duration elasticities (estimated by sample enumeration)

Elasticity with respect to:	Male	Female
Number of miles driven per year	−0.595	−0.504
Annual household income	0.474	0.547
Total accumulated years of driving experience	—	0.302
Total accumulated miles of driving experience	0.357	—
Number of years past 16 years of age, began driving	—	−0.127

The second explanation for the income coefficient is that higher income drivers may own safer vehicles (i.e. their brakes, steering, and tire quality may help them avoid accidents), although this is not a particularly strong explanation since historical data indicates that relatively few accidents can be traced to vehicle defects. Finally, the third explanation is that higher income drivers may live in residential areas and conduct work and recreational activities in areas that offer them less exposure to accident risk. This is purely speculative since no residential information was collected to support this assertion.

A number of key variables underscore the differences between male and female drivers. For males, a record of moving violations was found to decrease the duration until accident occurrence, whereas for females, a record of previous accidents performed a similar function. With the limited data sample available, it is not possible to arrive at defensible explanations for these differences. It is speculated that moving violations and accident involvement are capturing gender differences in risk-taking behavior.

The older females were when they first became licensed drivers (as indicated by the "number of years past 16 years of age, began driving" variable), the more likely they were to have an accident (i.e. shorter duration until accident occurrence). In a sense, this is potentially capturing a self-selection process in that individuals who have poor driving skills and/or a fear of driving are likely to wait longer to become licensed and have a higher accident risk once licensed. This effect was not found to be significant for male drivers. A possible explanation for this is that older males may have underreported accident involvement, although the sample offers no evidence to support this possibility.

In terms of the effect that experience had on accident risk, it was found that male accident risk declined (i.e. longer durations until an accident) as more total miles were accumulated and that female accident risk declined simply as more years of driving experience were accumulated (both were inelastic, as shown in Table 3). While this finding underscores important differences between the sexes with regard to the driving experience/accident risk relationship, defensible explanations for this are likely hidden in more disaggregate data, such as the types of roads each sex typically drives on, under what conditions they typically drive (e.g. husbands may drive in adverse conditions), and so on.

Finally, one of the most interesting findings of this study is the value of the duration parameter for both male and female hazard models. For the male model, the duration parameter (ρ in Eqn 6) is significantly less than one (95% confidence interval is 0.629 to 0.989), indicating a hazard decreasing in duration. In words, this says that the longer a male driver goes without having an accident, the less likely he is to have an accident. For the female model, the duration parameter is not significantly different from one (95% confidence interval is 0.790 to 1.406) indicating a constant hazard and implying that the likelihood of a female having an accident is independent of the time that has transpired without having an accident. (Note that, due to the relationship between Weibull and exponential distributions, a Weibull distribution with a duration parameter of one reduces to the "memoriless" exponential distribution, i.e. $f(t) = \gamma \exp[(-\gamma t)]$.) This finding, in all likelihood, would not be significantly affected by possible male underreporting of accidents, since such underreporting would primarily impact the magnitude of the hazard function and not the shape. Also, the decreasing hazard function for males does not imply that aggregate accident data should reveal a higher proportion of males who have never been accident-involved relative to females. Again, the magnitude of the hazard could easily mask any shape effects in aggregate accident data.

Differences between male and female duration-dependent accident risk is very suggestive and gives rise to some important questions. For example, what is it about males that allows them to reduce their accident risk the longer they go without having an accident and why do females not exhibit this same tendency? Are there some fundamental differences between the way men and women collect and process information relating to driving experience that could explain this phenomenon? Or, is this simply capturing the fact that young males start out as such reckless drivers that their risk-taking behavior naturally adjusts downward over time in a way that cannot be captured by the covariates included in the model?

While the findings of this paper are suggestive, answers to the above questions will require quite a substantial research effort particularly in terms of data collection (i.e. using an extensive sample of individual's actual accident records). Also, the joint participation of statistical, psychological, physiological, and human factor research disciplines is vital to unraveling important gender differences.

SUMMARY AND CONCLUSIONS

This paper has presented a brief overview of gender differences in the driver-characteristic/accident-risk relationship and described some of the problems (particularly confounding correlation problems) that confront research in this area. In an effort to address some of these problems, the hazard function approach is described and applied to a sample of University of Washington drivers. The model estimation results show that male and female drivers have significantly different driver characteristic/accident risk relationships.

From an insurance perspective, most companies use gender, age, accident records, moving violation records, and exposure as a basis for establishing premiums. The results of this study suggest that, by and large, insurance companies are using most of the key determinants of accident risk, however it is not clear that they are adequately accounting for the true multivariate nature of the problem. Indeed, the interaction between gender and the "classic" determinants of accident risk is a complex, statistically significant process, and one that is in need of continuing further study. Such study must necessarily involve a variety of academic disciplines and should lead us ever closer to that elusive combination of equitable, legally defensible insurance premiums.

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