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TECHNICAL
R E P O R T



Estimating the Accident Risk of Older Drivers

David S. Loughran, Seth A. Seabury



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Preface

This report estimates the relative risk posed by older drivers in the United States. Our computation of the relative risk posed by older drivers employs data compiled by the Bureau of Transportation Statistics' (BTS) Fatal Accident Reporting System (FARS) and a statistical procedure attributable to Levitt and Porter (2001). This report should be of particular interest to the insurance industry, public agencies, and private organizations concerned about driver safety and the welfare of older Americans. A companion paper to this report, *Regulating Older Drivers: Are New Policies Needed?* (Loughran, Seabury, and Zakaras, 2007), discusses how these estimates can inform the policy debate regarding older drivers.

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Summary

As the U.S. population ages, so will the population of licensed drivers. Policymakers are concerned that this aging of the driving population will lead to increases in traffic accidents and, consequently, injury to property and person. Although it is uncontroversial that the capacity to safely operate a motor vehicle decreases at older ages, we should expect at least some older individuals to voluntarily limit their driving when they perceive that their ability to drive has diminished. From a policy perspective, the question is whether the elderly self-regulate to the extent that their overall negative impact on traffic safety is no more than that of drivers of other ages.

The research reported here applies an innovative statistical procedure attributable to Levitt and Porter (2001) to estimate how the probability of causing an automobile accident varies with age.¹ At first glance, it might seem that computing this probability by age would be quite simple. All that is needed is to divide the number of automobile accidents caused by drivers of particular ages by a measure of their prevalence on the road (for example, vehicle miles traveled).

However, data needed to compute these statistics have a number of significant limitations. Data on automobile accidents are not collected consistently on a national basis and there is good reason to believe that a large fraction of accidents is never reported to either insurers or public authorities. Moreover, accident fault is not reliably recorded in accident data. Data on vehicle miles traveled are self-reported and error in those self-reports could increase with respondent age.

With appropriate modifications, the approach of Levitt and Porter (2001) allows us to compute the likelihood that an older individual will cause an automobile accident relative to the likelihood that a younger individual will cause an automobile accident employing only high-quality data on counts of two-car fatal accidents involving drivers of different ages. Fatal accidents are reliably reported in FARS. With this approach, we circumvent the problems inherent in using data on all accidents (fatal and nonfatal) and vehicle miles traveled.

Our estimates of what we call the *relative riskiness* of older drivers emerge from a model of the probability of observing fatal crashes between drivers of different types.² The derivation

¹ Levitt and Porter (2001) apply the statistical procedure to the problem of estimating how much likelier drunk drivers are to cause an accident than are sober drivers.

² We cannot distinguish between riskiness due to drivers taking greater risks and that due to declining driving ability or other factors, so *riskiness* throughout this report refers to both types of risk. In general, though, we assume that the increased

of these estimates is technical in nature, but the assumptions needed to formulate the model are transparent and reasonable. Most important, the model assumes that older and younger drivers are “equally mixed” on the road (i.e., older drivers are not disproportionately clustered temporally or geographically) and that older drivers are at least as likely to cause an accident as are younger drivers, where “younger” drivers are defined to be 25–64 years old and “older” drivers are defined to be 65 and older. The former assumption is supported by examining relative riskiness in specific locations and at specific points in time and the latter assumption is supported by studies of the physiology of driving.

Applying our model to FARS data from between 1975 and 2003, we find that drivers 65 and older are 16 percent likelier than drivers 25–64 years old to cause an accident. Given the reasonable assumption that driving ability should worsen as mental and physical conditions deteriorate, it might come as a surprise to some readers that our estimate of the relative riskiness of older drivers is not higher. It is important to recognize, however, that our estimates reflect the riskiness of older drivers who continue to drive. We suspect that the riskiest older drivers significantly limit how much they drive or choose not to drive at all so as to lower the risk that they might cause property damage or injure themselves or others. In other words, older drivers do, in fact, self-regulate.

This conjecture regarding self-regulation is supported by a number of additional findings. Conditional on being in an accident, we estimate that individuals riding in cars driven by older drivers are nearly seven times likelier to die in an auto accident than are individuals riding in cars driven by middle-aged drivers. Since the ages of passengers and drivers are highly positively correlated, this finding suggests that older individuals are much likelier to die in a car accident than are middle-aged individuals. Consequently, self-preservation provides considerable incentive for older individuals to curtail their driving (and perhaps car travel in general). And, in fact, our estimates imply just that: By our estimates, older licensed drivers drive only 60 percent as many miles as do middle-aged individuals.

Finally, we find that our estimate of relative riskiness actually falls between 55 and 70 years old. An explanation for the decline in relative riskiness between these ages is that self-regulation becomes increasingly effective with age. Only the healthiest and safest drivers continue to drive at more advanced ages.

An alternative to the self-regulation hypothesis is that state licensing regulations have succeeded in identifying the riskiest older drivers and discouraging them from driving. That is, in the absence of state licensing regulations targeted at older drivers, such as mandatory vision and road tests, accelerated and in-person renewal policies, and mandatory physician reporting of medical conditions to state licensing authorities, older drivers would be much riskier than we estimate them to be. However, this hypothesis is not supported by existing empirical evidence. Most studies find little or no correlation between measures of the riskiness of older drivers and the existence of specific state licensing policies. We also note that our estimates indicate that the relative riskiness of older drivers changed little between the early 1970s and the last period of our data, 1998–2003, a time during which many states adopted more stringent licensing requirements for older drivers.

riskiness of older drivers is due to their declining ability rather than an increased likelihood of taking chances.

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Glossary

BTS	Bureau of Transportation Statistics
crash fatality rate	$\frac{\text{number of fatal accidents}}{\text{number of all accidents}}$
crash incidence rate	$\frac{\text{number of all accidents}}{\text{number of licensed drivers}}$
exposure rate	$\frac{\text{number of licensed drivers}}{\text{vehicle miles traveled}}$
FARS	Fatal Accident Reporting System
fatal crash rate	$\frac{\text{number of fatal accidents}}{\text{number of licensed drivers}}$
FHWA	Federal Highway Administration
GES	General Estimate System
ICJ	Institute for Civil Justice
i.i.d.	independently and identically distributed
NHTS	National Household Travel Survey
OLS	ordinary least squares
relative crash fatality rate	likelihood that an occupant in a car driven by a driver of type i will die in an accident relative to the likelihood that an occupant in a car driven by a driver of type j will die in an accident
relative exposure	prevalence on the road of a group of drivers of type i relative to the prevalence on the road of a group of drivers of type j

relative riskiness likelihood that a group of drivers of type i will cause an accident
relative to the likelihood that a group of drivers of type j will
cause an accident

VMT vehicle miles traveled

Introduction

The fraction of licensed drivers 65 and older in the United States increased from 10 to 14 percent between 1975 and 2001 and is expected to continue rising over the next several decades.¹ This fraction is increasing both because the U.S. population is aging—the U.S. Census Bureau estimates that individuals 65 and older will account for 19 percent of the U.S. population in 2025, up from 13 percent in 2000—and because the fraction of older Americans licensed to drive is increasing. The sheer number of older licensed drivers on the road will surely continue to rise as the population ages and economic forces (e.g., suburbanization, later retirement) make driving increasingly important for maintaining social and economic relationships at older ages.

Although driving is certainly important to older individuals, there is a legitimate concern that older drivers pose a significant injury risk to both themselves and to other drivers. On July 16, 2003, an 86-year-old man inadvertently drove his 1982 Buick into a crowd of pedestrians shopping at an open-air farmers' market in Santa Monica, California, killing 10 and injuring more than 50. This and other terrible traffic accidents involving older drivers has reinvigorated a long-simmering debate over the riskiness of older drivers and state-level licensing policies aimed at screening out the most dangerous of these drivers.²

Aging entails a variety of physical and mental changes that impair driving ability. Worsening vision can be particularly problematic for driving. The incidence of glaucoma, macular degeneration, and cataracts all increase with age. These diseases can reduce night and peripheral vision and vision acuity and cause individuals to become more sensitive to glare (Voelker, 1999). Normal changes in brain functioning slow reflex reactions and reduce the ability to multitask and take in information from disparate sources simultaneously (Ponds, Brouwer, and Van Wolffelaar, 1988). More-severe changes in brain functioning, such as depression and dementia and the medications used to treat those illnesses, may seriously hamper an older individual's ability to drive, as will other common afflictions of older individuals, such as heart disease, arthritis, and insomnia (Uc et al., 2004).

¹ Authors' computations from data on licensed drivers by age and year reported by the Federal Highway Administration (FHWA).

² For example, in October 2005, a 93-year-old man thought to be suffering from dementia struck a pedestrian in St. Petersburg, Florida, and did not notice the corpse on his windshield until a tollbooth operator stopped him ("National Briefing," 2005).

Thus, it is uncontroversial that the capacity to safely operate a motor vehicle decreases at older ages, but this fact alone does not necessarily mean that older drivers as a class are riskier than younger drivers. The reason for this is that, to some extent, older individuals self-regulate, removing themselves from the road when they believe they can no longer operate a motor vehicle safely. From a policy perspective, the question is whether this self-regulation is sufficient.

Consider an older individual who must decide whether to drive to the grocery store. We should expect that individual to weigh the private benefit and cost of driving to the store versus other modes of transportation (e.g., walking, taking the bus). Importantly, the cost of driving to the grocery store includes the risk of getting into an accident and suffering an injury oneself. Thus, older drivers, like all rational drivers, will account for their own likelihood of suffering injury (whether it be the result of their own or someone else's driving error) in deciding whether (or how much) to drive.³

However, it is much less likely that the older individual, when deciding whether to drive, will fully account for the potential harm that he or she might inflict on other drivers and passengers. That is, the full *social* costs of driving are not accounted for in the *private* decision to drive.⁴ Standard economic arguments then imply that older drivers drive more (and more than is socially optimal) than they would if they fully internalized the expected cost to others (the social cost) of their decision to drive (see, for example, Edlin and Karaca-Mandic, 2006).

This failure to fully internalize the expected social cost of driving is not unique to older drivers. Indeed, it is likely that the vast majority of drivers, young and old, fail to account for the full expected social cost of their decision to take a particular trip by car, which means that all drivers likely drive more than is socially optimal. But the degree to which a particular class of driver drives too much increases with the likelihood that the class will cause an accident.⁵ And, as social and private costs of driving diverge, so do the privately and socially optimal levels of driving.

Nonetheless, there is evidence that older individuals do compensate for their driving limitations by, for example, driving less frequently, and when they do drive, driving at lower speeds and during daytime hours (Baldock et al., 2006; Vance et al., 2006; Stutts, 1998; Jorgensen and Polak, 1993; Kington et al., 1993; Foley et al., 2002; Marottoli et al., 1993). And, of course, individuals eventually do decide to stop driving altogether, both because they (or a relative, doctor, or state agent) recognize that they are likelier to cause an accident and because

³ A caveat to this would be if seniors underestimated the risk they posed to themselves, which may justify public policy in a paternalistic sense. Although this may very well be true for those with some kind of cognitive ailment, it is not obvious why this would be true for the vast majority of seniors. And, in fact, our results on self-regulation would seem to suggest the opposite.

⁴ There are many social costs of driving, but here we mean specifically those costs related to personal injury and property damage.

⁵ Some simple algebra makes this point. Suppose that there are n drivers on the road and that one of those drivers is an older driver. The probability that one of the drivers will cause an accident with one other driver is $0 \leq p \leq 1$. If the cost to the driver of causing such an accident is c , then the private expected cost of driving is simply $p \times c$. If all drivers on the road are equally likely to be involved in an accident with this one driver and the cost of being in the accident for all of those drivers is d , then the expected social cost of driving is $[p/(n-1) \times (n-1) \times d] + p \times c = p(c+d)$. So the difference between social and private costs is $p \times d$, which increases as drivers become riskier (i.e., as p increases).

they themselves are likelier to be harmed should they be in an accident, regardless of fault. But is this self-regulation enough? Or do older drivers as a class pose sufficiently high risks to other drivers to warrant a specific policy response? To answer this question, we need to know whether those older individuals who do continue to drive are, in fact, riskier on average than younger drivers. If so, then we might argue that states should be more aggressive in identifying risky older drivers and limiting their right to drive. If not, then we might conclude that current policy coupled with self-regulation is sufficient.

This research applies an innovative statistical procedure attributable to Levitt and Porter (2001) to estimate how the probability of causing an automobile accident varies with age.⁶ At first glance, it might seem that computing this probability by age would be quite simple. All that is needed is to divide the number of automobile accidents caused by drivers of particular ages by a measure of their prevalence on the road (for example, vehicle miles traveled, or VMT).

However, statistics of this sort based on high-quality data are not readily available. Data on automobile accidents in general are not collected consistently on a national basis and there is good reason to believe that a large fraction of accidents is never reported to either insurers or public authorities. Data on VMT are collected via survey every five years by the National Household Travel Survey (NHTS). These VMT data are undoubtedly measured with some error. Moreover, sample sizes are too small to produce reliable temporally and geographically disaggregated estimates of VMT by age. Data quality issues aside, accidents divided by VMT may not accurately reflect differences in the likelihood of causing an accident, which is what we are most interested in knowing. This is because accident fault is often difficult to establish and, consequently, not recorded reliably in accident data.

If the measurement error resulting from these data quality issues was purely random, this would not necessarily prevent us from accurately estimating age-specific differences in the likelihood of causing an accident. However, we think it is unlikely that the error is random. The likelihood that an accident will be reported to the police is much greater if an individual is injured in the accident. Since older drivers are likelier to be injured in an accident than are younger drivers, accident counts are likelier to overestimate the number of accidents caused by older drivers than they are to overestimate the number of accidents caused by younger drivers. Thus, the greater fragility of older drivers will make them appear riskier than they really are.

The approach of Levitt and Porter (2001) circumvents the data quality problems by relying only on readily available, high-quality data on the relative frequency of two-car fatal accidents involving different combinations of driver types⁷ and the fact that the opportunities for various two-car crash types are dictated by the binomial distribution. Of course, counts of fatal accident data are vulnerable to a similar problem, that older individuals are likelier than younger ones to be injured (or killed) in a crash, so crashes involving older drivers will be over-represented in our data. Under a reasonable set of assumptions, which we detail below, the sta-

⁶ Levitt and Porter (2001) apply the statistical procedure to the problem of estimating how much likelier drunk drivers are to cause an accident than are sober drivers.

⁷ As described in the next chapter, we employ data from the Fatal Accident Reporting System (FARS), an annual census of all fatal accidents involving motor vehicles in the United States.

tistical method can be modified to consistently estimate what we call the relative riskiness (i.e., the likelihood that older drivers will cause an accident relative to younger drivers) and relative exposure of older drivers (i.e., the prevalence of older drivers on the road relative to younger drivers) independent of the relative fatality risk (i.e., the likelihood that older drivers will be killed in a crash relative to younger drivers).

The next chapter of this report presents descriptive statistics on older drivers and reviews the relevant literature. Chapter Three describes the statistical model of Levitt and Porter (2001) and how we modify their model to compute relative riskiness and relative exposure of older drivers. Chapter Four discusses the data used in this report. Chapter Five presents estimates of the relative riskiness and exposure of older drivers as derived from the Levitt and Porter (2001) model, compares them to previously published estimates of riskiness and exposure, and explores how these estimates vary with accident circumstances. The report concludes in Chapter Six.

Measuring Relative Riskiness

Prior studies of older drivers have estimated the relative riskiness of older drivers by relying solely on data on fatal and nonfatal accidents, licensed drivers, and VMT. In this chapter, we explain that these simple measures of relative riskiness can conflate relative riskiness with two other features of driving behavior that change with age, namely, exposure and fragility (i.e., the likelihood of being injured in an accident conditional on being in an accident).

Decomposing the Fatal Crash Rate

The most readily computable measure of driver risk is fatal accidents, F , per licensed driver, N , which we will call the fatal crash rate. Fatalities are recorded in the Bureau of Transportation Statistics' (BTS') FARS, which records information on all accidents that occur on public roads in the United States that lead to a death within 30 days of the accident.¹ The FARS data, available from 1975 onward, are derived from reports produced by state transportation agencies that collect information about fatal accidents from medical examiners, coroners, and emergency medical and police accident reports; the data are widely considered to represent a complete census of fatal automobile accidents in the United States. The number of licensed drivers by age is also available from administrative sources.²

In Figure 2.1, we see that the fatal crash rate has a U-shaped age pattern.³ Both relatively young and relatively old licensed drivers have an elevated likelihood of being killed in an accident. In 2000, the fatal crash rate of drivers 20–24 years old was more than twice as high as the fatal crash rate of drivers 50–59 years old. The fatal crash rate of drivers 84–89 years old was about one-third higher than the fatal crash rate of drivers 50–59 years old.

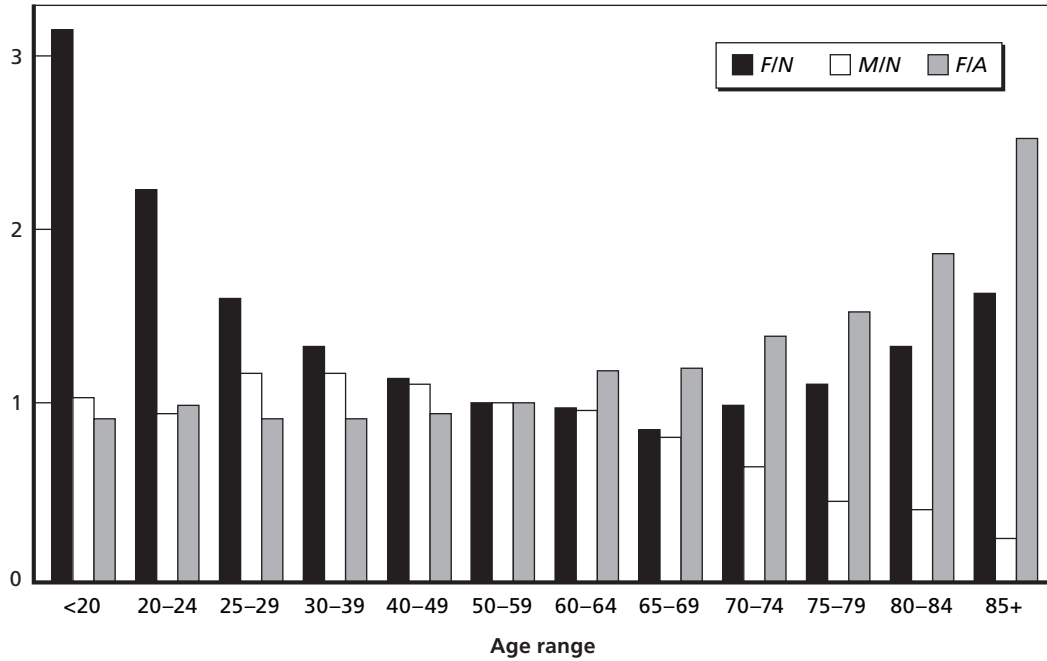
Although readily computable, the fatal crash rate itself is not particularly informative. This is because the fatal crash rate is a function of a number of underlying factors, all of which are relevant to assessing the riskiness of older drivers. In the following equation, we decompose the fatal crash rate into three parts: (1) the likelihood that individuals in a given class will die in an

¹ Detailed information about FARS can be found in Tessmer (2002).

² These data can be found in the FHWA's *Highway Statistics* (U.S. Public Roads Administration, U.S. Bureau of Public Roads, and U.S. Federal Highway Administration, annual).

³ Our numerator, F , counts fatal accidents involving a driver of age i .

Figure 2.1
Normalized Fatal Crash, Exposure, and Crash Fatality Rates, by Age



SOURCE: Authors' calculations based on fatality data from the 2000 FARS, 2000 data on licensed drivers from FHWA, VMT data from the 2001 NHTS, and accident data from the 2000 General Estimate System (GES).

NOTES: F = number of fatal accidents involving driver of age i ; N = number of licensed drivers; M = vehicle miles driven; A = number of accidents involving driver of age i . Each rate is relative to the corresponding rate for drivers ages 50–59.

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accident, should an accident occur; (2) the underlying propensity of a given class of drivers to be in an accident; and (3) the exposure of that class to the possibility of an accident:

$$\frac{F_i}{N_i} = \frac{F_i}{A_i} \times \frac{A_i}{M_i} \times \frac{M_i}{N_i}, \quad (2.1)$$

where A_i is the number of fatal and nonfatal accidents, M_i is the number of miles driven, and i indexes class of driver. Following Dellinger, Langlois, and Li (2002), we refer to the three terms on the right side of the equation respectively as the crash fatality rate, the crash incidence rate, and the exposure rate (i.e., fatal crash rate = crash fatality rate \times crash incidence rate \times exposure rate).

In Figure 2.1, older drivers' elevated fatal crash rate, then, could be attributable to their greater fragility, an increased likelihood of causing an accident, or driving more miles. We do know that older drivers drive less than younger drivers, so this latter explanation is doubtful. As seen in Figure 2.1, which employs data on VMT from the 2001 NHTS, the exposure rate (M/N) falls steadily with age after ages 30–39. Miles driven could fall with age for many rea-

sons, including a fall in work-related driving, an increase in demand for entertainment closer to home, or because deteriorating health and driving ability require that they drive less.

There is, however, considerable evidence that the crash fatality rate increases with age. On average, older individuals are more susceptible to the wide range of trauma experienced in an automobile accident (Evans and Gerrish, 2001; Kim et al., 1995; Augenstein, 2001). One proxy for the crash fatality rate is the ratio of the number of driver fatalities (computed from FARS) to the number of accidents of all types (computed from GES) (Li, Braver, and Chen, 2003). We show this statistic by age in Figure 2.1. By this measure, compared with drivers 50–59 years old, drivers 65–69 years old are 21 percent likelier to die in a motor vehicle accident; drivers 84–89 years old are 86 percent likelier to die in a motor vehicle accident.

An alternative measure of the crash fatality rate devised by Evans (1988) compares differences in fatality rates between drivers and passengers riding in the same car but of different ages. This approach effectively controls for differences in the types of accidents experienced by individuals of different ages. By this measure of the crash fatality rate, Evans (1988) also finds that the likelihood of dying in a motor vehicle accident increases steadily with age; at age 70, the crash fatality rate is about three times the crash fatality rate at age 20.

The importance of accounting for both exposure and the crash fatality rate in interpreting age-related trends in the fatal crash rate can be seen in Figure 2.2, in which we graph, by age, fatalities divided by VMT (F/M) and police-reported accidents divided by VMT (A/M), both normalized to the corresponding rates for drivers 50–59 years old. The U-shaped pattern in F/M is more pronounced at older ages than the U-shaped pattern in the crash fatality rate (F/N), reflecting the fact that older licensed drivers drive fewer miles than do younger licensed drivers. But the strong upswing in F/M at older ages could be due to the sharp increase in the crash fatality rate (F/A). The fact that police-reported accidents divided by VMT (A/M) increase more slowly with age supports this conjecture.

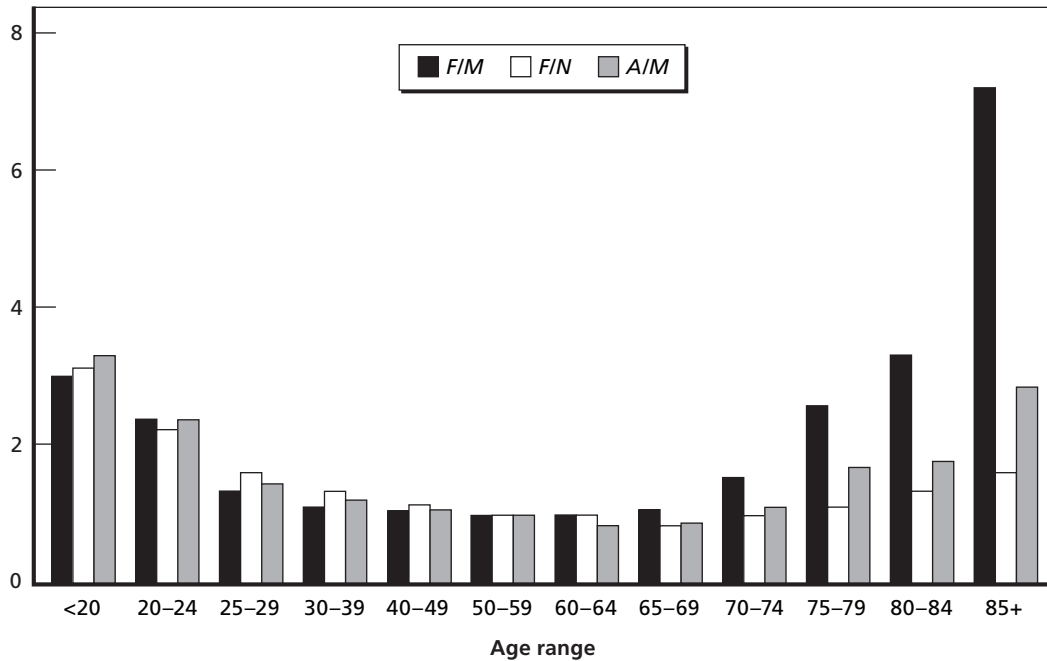
Data Quality

To summarize, national statistics suggest that the fatal crash rate increases with age, in part because older drivers are likelier to die than are younger drivers if they are involved in a motor vehicle accident. According to these statistics, those older individuals who choose to drive are somewhat likelier to get into an accident than are younger drivers, but they are far likelier to die when they do get into an accident.⁴ Thus, even though we have good reasons to believe that driving ability declines with age, it would appear from the evidence summarized here that some combination of private self-regulation and public policy causes individuals whose driving abilities have deteriorated most severely to curtail their driving.

However, although the data on fatal accidents and licensed drivers are quite good, the data on accidents more broadly and VMT are not, which causes us to question whether inferences based on these data are reliable. Unlike for fatal accidents, a state-by-state census of all automobile accidents is not available. The BTS does maintain data on a nationwide sample of

⁴ Evans (1988); Lyman et al. (2002); and Li, Braver, and Chen (2003) come to a similar conclusion.

Figure 2.2
Normalized Fatal Crash and Nonfatal Crash Rates, by Age



SOURCE: Authors' calculations based on fatality data from the 2000 FARS, 2000 data on licensed drivers from FHWA, VMT data from the 2001 NHTS, and accident data from the 2000 General Estimate System (GES).

NOTES: F = number of fatal accidents involving driver of age i ; N = number of licensed drivers; M = vehicle miles driven; A = number of accidents involving driver of age i . Each rate is relative to the corresponding rate for drivers ages 50-59.

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accidents from local police reports beginning in 1988 in the GES, but these samples are not likely to be representative of all accidents, since many accidents are not reported to the police. Particularly problematic from our standpoint is the likelihood that accidents involving a serious injury are likelier to be reported to the police and, as just noted, older individuals involved in a crash are probably more susceptible to injury. Moreover, the accident data do not provide a credible way of determining who was at fault in the accident. Thus, although the data might show that some class of individuals appears to be involved in more accidents, we cannot say for certain whether this class of individuals in fact causes more accidents.

The empirical approach we describe in the following chapter requires only data on fatal accidents to estimate the relative crash incidence rate, or “relative riskiness,” of older drivers. In this way, we circumvent the need to use data on accidents more broadly, which we have just argued are problematic for a number of reasons, and data on self-reported VMT, which are also likely measured with error.⁵

⁵ As noted in Chapter One, VMT is self-reported in the NHTS. The error in self-reported VMT could be correlated with age. The survey is conducted approximately every five years with the last survey conducted in 2001.

Derivation of an Alternative Estimate of Relative Riskiness and Exposure

In this chapter, employing only data on fatal two-car crashes, we explain how we estimate the relative riskiness, exposure, and crash fatality rates of older drivers. With the exception of two relatively minor modifications, our analytical approach and much of its exposition is taken directly from Levitt and Porter (2001). Our modifications include (1) an extension of the approach to three types of drivers and (2) an allowance for differential crash fatality rates.

Because the exposition of the empirical model is technical in nature, we first provide a conceptual overview of the model accessible to the general audience. The overview defines the parameters we report in Chapter Five, describes the basic intuition behind the empirical model, and highlights the key assumptions that must be maintained to interpret the parameters of the model as we do in Chapters Five and Six. The second part of this chapter provides a formal exposition of the empirical model and details its assumptions.

A Conceptual Overview of the Empirical Model

The empirical model uses data on fatal two-car crashes between younger, middle-aged, and older drivers to estimate the relative riskiness, relative exposure, and relative crash fatality rates of older drivers.¹ For clarity of exposition, we define only two classes of drivers here, younger and older. The extension of the model to three classes of drivers is straightforward and is described in the second part of this chapter.

¹ More precisely, the model estimates the relative likelihood of causing a two-car accident. Like Levitt and Porter (2001), we could also back out the relative likelihood of causing a one-car accident using our estimate of the relative likelihood of causing a two-car accident. However, we have little reason to believe that these relative likelihoods differ from one another (Levitt and Porter show that, in the case of drunk drivers, there is virtually no difference between the relative likelihoods of causing one- and two-car crashes). Note that, since the estimate of the relative likelihood of causing a one-car crash is derived using the estimate of the relative likelihood of causing a two-car crash, the one-car crash estimates do not offer any independent validation of the two-car crash estimates.

We define the relative riskiness of older drivers as

$$\bar{\theta}_o = \frac{\frac{A_o}{M_o}}{\frac{A_y}{M_y}}, \quad (3.1)$$

where A_i is the number of two-car accidents caused by driver type i (younger, Y , or older, O) and M_i is VMT of driver type i . Thus, relative riskiness measures how much likelier or less likely older drivers are than younger drivers to cause a two-car accident per vehicle mile driven. Relative exposure is defined as

$$\bar{N}_o = \frac{M_o}{M_y} \quad (3.2)$$

and measures how many opportunities older drivers have to be involved in a two-car crash relative to younger drivers. Finally, the relative crash fatality rate is defined as

$$\bar{\pi}_o = \frac{\frac{F_o}{A_o}}{\frac{F_y}{A_y}}, \quad (3.3)$$

where F_i is the number of drivers of type i killed in automobile accidents and A_i measures all two-car accidents involving driver type i . The relative crash fatality rate tells us how much likelier older drivers are than younger drivers to die in an accident.

The method we use to compute older drivers' relative riskiness and exposure is perhaps best understood by considering the following example, in which we assume that the relative crash fatality rate is 1. Suppose that, over some stretch of road at some particular point in time, there are five younger drivers and three older drivers. Each of these drivers has one chance in five of causing an accident with another car that he or she passes on the road. If we were to observe an interaction between two of these drivers, we then ask, what is the probability that these two drivers crash into each other and that the two drivers are both young, both old, or one driver is young and the other driver is old? Under the assumption that the two types of drivers are equally mixed among one another, this is equivalent to asking what the probability is of drawing two balls of given types from an urn containing two types of balls (for example, red and white balls).

The assumption of "equal mixing" requires that there be no "bunching" of drivers in space or time. The assumption is violated if, for example, older drivers are likelier to interact with other older drivers for each mile driven than they are to interact with younger drivers, perhaps because they frequent the same locations or drive at the same times of day. The equal

mixing assumption, therefore, becomes increasingly plausible as the level of geographic and temporal disaggregation becomes increasingly detailed. Levitt and Porter (2001) demonstrate that violation of the equal mixing assumption will result in downwardly biased estimates of θ_o and upwardly biased estimates of N_o under their model. Our, and their, approach to minimizing the effect of this particular bias is to disaggregate the data as much as sample sizes will permit. This issue is discussed further in Chapters Four and Five.

In example A in Table 3.1, under the assumption of equal mixing, it turns out that the probability of observing two younger drivers crash into each other is 0.16, the probability of observing two older drivers crash into each other is 0.06, and the probability of observing a younger and an older driver crash into each other is 0.19. The assumption of equal mixing here is critical to computing these particular probabilities. Without this assumption, the probabilities would not be a simple function of the relative numbers of drivers on the road and their relative probabilities of causing an accident. The equations that generate the probabilities listed in the top panel of Table 3.1 from the assumed parameters listed in the bottom panel of that table are derived in the second part of this chapter.

Now suppose that younger drivers crash into one out of five cars they pass, but older drivers crash into two out of five cars they pass (example B, Table 3.1). In this case, we would find that the probability of observing two younger drivers crash into each other is still 0.16, the probability of observing two older drivers crash into each other has increased to 0.11, and the probability of observing a younger and an older driver crash into each other has increased to 0.28. As expected, then, when the relative riskiness of older drivers increases, the probability that we observe crashes involving older drivers increases.

The probability of observing crashes involving older drivers also increases if the relative exposure of older drivers increases (example C, Table 3.1). For example, suppose, as in example A, that older and younger drivers crash into one out of five cars they pass, but that now there are five, instead of three, older drivers. The probability of observing two younger drivers crash

Table 3.1
The Probability of Observing Crashes Involving Younger and Older Drivers

Accident Type	Probability of Observing Crash		
	Example A	Example B	Example C
Young and young	0.16	0.16	0.10
Old and old	0.06	0.11	0.10
Young and old	0.19	0.28	0.20
Assumed Parameters			
Crash probability (young)	0.2	0.2	0.2
Crash probability (old)	0.2	0.4	0.2
Young drivers	5	5	5
Old drivers	3	3	5

is now 0.10, the probability of observing two older drivers crash is also 0.10, and the probability of observing a younger and an older driver crash is 0.20.

Now let us suppose that all we observe is simple counts of two-car crashes between older and younger drivers, which is what we in fact observe in the FARS data. The empirical model of Levitt and Porter (2001) essentially asks what relative riskiness and exposure rates are consistent with these observed counts under the assumption that the counts of fatal crashes are generated from the probabilistic model just described. Table 3.2 lists counts of different accident types and the relative riskiness and relative exposure they imply. For example, a relative riskiness of 2.0 and exposure rate of 0.6 are consistent with counts of 16 crashes between two younger drivers, 11 crashes between two older drivers, and 28 crashes between a younger and an older driver as in example A.

That we can make these inferences from these simple counts might seem strange, given that we required four pieces of information to generate the probabilities listed in Table 3.1: the riskiness of younger and older drivers and the exposure of younger and older drivers. For example, suppose the number of crashes between two older drivers doubles from 11 (as in example A, Table 3.2) to 22 (as in example B). This higher number of crashes between two older drivers would appear to be consistent with the possibility that older drivers are both relatively riskier and more numerous.² Working through the formal exposition of the empirical model later in this chapter, in which we show that the problem's mathematics imply that there are more equations generating probabilities of observing different crash types than there are unknown parameters, is the most convincing basis we have for drawing these inferences from the count data, but we provide some intuition here.

Table 3.2
Relative Riskiness and Exposure Consistent with Counts of Fatal Crashes Involving Younger and Older Drivers

Accident Type	Number of Observed Crashes		
	Example A	Example B	Example C
Young and young	16	32	11
Old and old	11	22	16
Young and old	28	56	28
Estimated Parameters			
— θ_o	2.0	2.0	2.0
— N_o	0.6	0.6	0.6

² Levitt and Porter (2001) liken this to trying estimate free-throw percentages in basketball without knowing the number of free-throw attempts.

First, we note that the model can identify only relative riskiness and exposure. Thus, the count data can identify two, not four, parameters. This makes sense, since it is the relative, not absolute, number of crashes of different types that are used to compute the relative riskiness and exposure parameters. For example, the relative riskiness of older drivers is still 2.0 and the relative exposure of older drivers is still 0.6 in example B (Table 3.2), in which the number of crashes of different types has been doubled in all categories (i.e., 32, 22, and 56).

Second, the empirical model forces us to assume that older drivers are at least as risky as younger drivers, in the sense that they are at least as likely to make a mistake that results in a crash. The fact that we need to make this assumption can be appreciated in part by looking at example C in Table 3.2, in which the number of crashes between two younger drivers is 11, the number of crashes between two older drivers is 16 (the reverse of example A, Table 3.2), and the number of crashes between older and younger drivers is 28, but the implied relative riskiness of older drivers is still 2.0 and their relative exposure is still 0.6. Without making the assumption that older drivers are riskier than younger drivers, the count data cannot tell us which class of driver is riskier, since we do not know from the count data alone whether the elevated number of young-young crashes is due to the fact that there are more young drivers on the road or because younger drivers are likelier to cause crashes.

As stated previously, it is uncontroversial that cognitive and physical degeneration with age lowers driving ability and, although we might expect those individuals whose capabilities are most compromised by age to stop driving, drive less, or drive more carefully, it seems unlikely that this behavioral change would be strong enough to more than counteract the direct negative impact of aging. In the case of younger drivers, the negative impact of inexperience and immaturity on driving ability seems very likely to outweigh any positive impact that better physical and possibly cognitive capacities might have on driving ability. The data on accidents per VMT (Figure 2.2, Chapter Two) are also suggestive that younger and older drivers are, in fact, riskier on average than middle-aged drivers.

Levitt and Porter (2001) applied their model to the case of drunk and sober drivers, assuming that the two classes of drivers have the same crash fatality rate. This assumption is not appropriate in our case, since it is well established that older individuals are likelier to die, conditional on being in an accident, than are younger individuals. If we ignore the possibility that older drivers are likelier to die as a result of an accident than are younger drivers (i.e., if we assume that $\pi_o = 1$), our estimates of $\bar{\theta}_o$ will be biased upward. Intuitively, this is because the model assumes that differences in counts of older and younger drivers in our data vary because of differences in the likelihood of causing an accident and differences in numbers of drivers on the road, not because younger and older drivers have different likelihoods of dying once they get into an accident.

The final section of this chapter shows how we modify the Levitt and Porter (2001) approach to account for the likelihood that $\pi_o \neq 1$. We estimate π_o by taking the ratio of the probability that an individual (driver or passenger) is killed in the car of an older driver in a two-car accident between an older and younger driver to the probability that an individual (driver or passenger) is killed in the car of a younger driver in a two-car accident between an older and younger driver. The reason for using this particular estimate of π_o is detailed in the final section of this chapter.

Formal Development of the Model

We present the formal derivation of the empirical model in four sections. First, we derive the equations that describe the conditional probability of observing a fatal accident of a given type. We then discuss how these equations can be used to estimate relative riskiness and exposure using data on counts of fatal accidents. Then we explain how we estimate the relative crash fatality rate. Finally, we explain how we estimate standard errors.

As already noted, we need to make a number of assumptions to estimate relative riskiness and exposure from the fatality data alone. We discuss these assumptions as they arise in the formal development of the empirical model and how the violation of these assumptions would bias our results. Table 3.3 lists each of the key assumptions of the model.

The Conditional Probability of Observing a Fatal Accident of a Given Type

We denote three types of drivers: young (Y), middle-aged (M), and old (O). The number of miles driven by each type is given by N_Y , N_M , and N_O , respectively.³ Let N equal the total number of miles driven by all three types, so $N = N_Y + N_M + N_O$.

An important assumption of the Levitt and Porter (2001) model is that the probability of observing a driver of one type, i , and another type, j , at the same moment in time is simply the product of the probabilities that we will observe either type of driver. As noted by Levitt and Porter, interactions between type- i and type- j drivers in this model are logically equivalent to randomly drawing balls labeled i and j from an urn. Formally, we assume, conditional on an interaction ($I = 1$) between drivers of types i and j , that

$$\Pr(i | I = 1) = \frac{N_i}{N} \quad (3.4)$$

and

$$\Pr(i, j | I = 1) = \frac{N_i N_j}{N^2}. \quad (3.5)$$

This assumption, which we will refer to as the *equal mixing* assumption, requires that there be no bunching of drivers in space or time. The assumption is violated if, for example, older drivers are likelier to interact with other older drivers for each mile driven than they are to interact with younger drivers, perhaps because they frequent the same locations or drive at the same times of day. The reasonableness of the equal mixing assumption, therefore, increases as the level of geographic and temporal disaggregation becomes increasingly detailed.

³ We define exposure in our model in terms of number of miles driven rather than number of drivers on the road, as in Levitt and Porter (2001). More precisely, the Levitt and Porter model provides an estimate of the relative number of *opportunities* for two-car fatal crashes, which, in our case, we think is best approximated by the relative number of miles driven.

Table 3.3
Assumptions Necessary to Estimate Relative Riskiness, Exposure, and Fatality Risk Using Counts of Fatal Crashes Involving Younger and Older Drivers

Assumption	Explanation	Implication
Exactly three types of drivers (young, middle-aged, and old) exist.	This assumption limits the number of classes of drivers. Limited sample sizes make this assumption necessary.	Our estimates represent a weighted average of relative riskiness among those individuals who drive in each class.
Equal mixing applies.	Drivers of different classes are equally mixed on the road (i.e., there is no clustering of drivers of different types, geographically or temporally).	This assumption becomes increasingly plausible as we examine more finely defined groups of drivers. Violation of the assumption will yield downwardly biased estimates of relative riskiness and upwardly biased estimates of relative exposure.
A single driver is wholly at fault for a given two-car accident.	The model assumes that only one driver causes a given accident rather than the plausible alternative that both drivers contributed to the occurrence of the accident.	If older drivers are less skilled at avoiding accidents initiated by younger drivers, our estimates of relative riskiness will be downwardly biased.
Older drivers are at least as risky as younger drivers.	To identify relative riskiness and exposure in this model, we must assume that older drivers are at least as likely as younger drivers to cause an accident.	Violation of this assumption will cause us to find that older drivers are riskier than younger drivers when, in fact, younger drivers are riskier than older drivers. The existing empirical and epidemiological literature suggests that this assumption is reasonable.
The composition of driver types in one fatal crash is independent of the composition of driver types in other fatal crashes.	This assumption allows us to characterize the joint distribution of driver types involved in fatal crashes by the multinomial distribution.	There is little reason to believe that this assumption would not hold. Even if the assumption fails, there is no reason to expect the failure to bias the estimate of relative riskiness in a particular direction.
The force from a crash that potentially results in physical trauma is distributed equally among the occupants of both cars.	This assumption allows us to base the probability that a fatality occurs on the minimum threshold for physical trauma of the occupants of the two cars.	Violation of this assumption will cause us to attribute differences in the relative fatality rate across drivers to fragility when those differences could be attributable to something else (for example, if younger drivers were likelier to drive safer cars).

Conditional on two drivers interacting (i.e., passing each other on the road), the probability that a fatal accident, F , occurs depends on the probability that at least one of the drivers makes a mistake that leads to an accident (denoted by θ and referred to as the *crash incidence rate*) and the probability that at least one person in one of the drivers' cars dies as a result of that accident (denoted by π and referred to as the *crash fatality rate*):

$$\Pr(F = 1 | I = 1, i, j) = \Pr(A = 1 | I = 1, i, j) \Pr(F = 1 | A = 1, i, j). \quad (3.6)$$

In two-car interactions, Levitt and Porter (2001) assume that the probability that one driver will make a mistake is independent of the probability that the other driver will make a

mistake. This assumption allows us to express the probability of a mistake conditional on an interaction between driver types i and j as

$$\Pr(A = 1 | I = 1, i, j) = \theta_i + \theta_j - \theta_i \theta_j. \quad (3.7)$$

Because the probability that either driver will make a mistake that causes an accident is very small, the probability that both drivers will make a mistake is extremely small,⁴ which allows us to approximate this conditional probability as

$$\Pr(A = 1 | I = 1, i, j) = \theta_i + \theta_j. \quad (3.8)$$

The assumption of independence is not likely to hold in the case of the fatal crash rate. When two cars crash, the nature of the accident (e.g., the speed of the cars, the location of the accident, road conditions) is likely to have some common influence on the probability that individuals in either car will die as a result. For instance, if one vehicle is traveling 70 miles per hour and crashes head on with the other vehicle, this will certainly affect the probability of death for individuals in both cars.

Suppose that, when a crash occurs, it results in a severity level ϕ that is common across both cars. Individuals in car i are killed if and only if ϕ is greater than some threshold τ_i . We assume that the threshold is a function of the characteristics of individuals in the car and that the threshold is weakly declining in the average age of each car's drivers and passengers $\tau_Y \geq \tau_M \geq \tau_O$. That is, we assume that older individuals are at least as susceptible to crash severity as are younger individuals. In our data, the average age of drivers and passengers increases strongly with the age of the driver. If we assume that ϕ is an independently and identically distributed (i.i.d.) random variable, the probability that an individual in car i will die is $\pi_i = \Pr(\phi > \tau_i)$, and the probability that an individual in either car will die is the maximum of π_i and π_j , then⁵

$$\Pr(F = 1 | A = 1, i, j) = \pi_i + \pi_j - \min(\pi_i, \pi_j) = \max(\pi_i, \pi_j). \quad (3.9)$$

The reasoning behind this equation is as follows. If fatalities were independent, the probability that someone in either car will die would be the union of the two events. In this case, however, we observe a crash if and only if the severity of the crash (which is, by assumption, equal across both cars) is greater than the severity threshold for either driver. In terms of whether a fatal crash is observed, it only matters whether one severity threshold is exceeded.

⁴ Levitt and Porter estimate that the interaction term is on the order of 10^{-18} .

⁵ Of course, within classes of individuals, thresholds might vary. So, we might model the probability that an individual of class i will die in an accident as $\Pr(\phi > \tau_i + \varepsilon_k)$. As long as ε_k is i.i.d, this will be analogous to the case Levitt and Porter (2001) discuss of driver heterogeneity; in this case, the model estimates can be interpreted as weighted averages of the parameters, with the weights being the relative number of each heterogeneous group.

Thus, the probability of a crash resulting in at least one fatality is simply the probability that crash severity exceeds the lesser of the two thresholds.

One further complication with the crash fatality rates is that these probabilities should depend on the nature of the accident and that the nature of the accident could depend on what types of drivers interact. For example, the probability that we will observe a fatality when two older drivers crash could be different from the probability that we will observe a fatality when an older and middle-aged driver interact because the speeds involved in the two accidents could differ. Therefore, we superscript these probabilities with the type of interaction:

$$\Pr(F = 1 | A = 1, i, j) = \max(\pi_i^{ij}, \pi_j^{ij}), \quad (3.10)$$

where π_i^{ij} is the probability that an individual in a car with driver i will die, conditional on an accident between cars with drivers of types i and j .

Under these assumptions about the crash incidence and crash fatality rates, we define the probability that we will observe a fatal accident in our data conditional on an interaction between type- i and type- j drivers as

$$\Pr(F = 1 | I = 1, i, j) \approx (\theta_i + \theta_j) \max(\pi_i^{ij}, \pi_j^{ij}). \quad (3.11)$$

Multiplying equations 3.5 and 3.11 gives us the probability of observing drivers of types i and j conditional on an interaction:

$$\Pr(i, j, F = 1 | I = 1) = \frac{(\theta_i + \theta_j) \max(\pi_i^{i,j}, \pi_j^{i,j}) N_i N_j}{N^2}. \quad (3.12)$$

Since our data provide us with counts of fatal accidents only, we need an expression for the probability of observing a fatal accident involving drivers of type i and j . Bayes' Rule provides us with this expression:

$$\begin{aligned} \Pr(i, j | F = 1) &= \frac{\Pr(i, j, F = 1 | I = 1)}{\Pr(F = 1 | I = 1)} \\ &= \frac{(\theta_i + \theta_j) \max(\pi_i^{i,j}, \pi_j^{i,j}) N_i N_j}{\left[\begin{array}{l} (\theta_Y + \theta_M) \pi_M^{Y,M} N_Y N_M \\ + (\theta_Y + \theta_O) \pi_O^{Y,O} N_Y N_O \\ + (\theta_M + \theta_O) \pi_O^{O,M} N_M N_O \\ + \theta_Y \pi_Y^{Y,Y} N_Y^2 + \theta_M \pi_M^{M,M} N_M^2 + \theta_O \pi_O^{O,O} N_O^2 \end{array} \right]}. \end{aligned} \quad (3.13)$$

Equation 3.13 gives an expression for the probability of observing a fatal accident involving each pair-wise combination of driver types, of which there are six (younger-younger, younger-middle-aged, younger-older, middle-aged-middle-aged, middle-aged-older, and older-older). These six nonlinear equations do not provide us with sufficient information to identify all 12 unknown parameters (the three θ_i s, three N_i s, and six π_i^{ij} s).

However, given crash fatality rates (see later in this chapter for an explanation of how we separately estimate these parameters), we can use these equations to identify relative crash incidence rates and relative exposure rates. To do this, we define crash incidence and exposure rates relative to those of middle-aged drivers:

$$\begin{aligned}\bar{\theta}_Y &= \frac{\theta_Y}{\theta_M} \bar{N}_Y = \frac{N_Y}{N_M} \\ \bar{\theta}_O &= \frac{\theta_O}{\theta_M} \bar{N}_O = \frac{N_O}{N_M}.\end{aligned}\tag{3.14}$$

and express the six conditional probabilities represented by equation 3.13 accordingly:

$$\begin{aligned}P_{YY} &= \frac{\bar{\theta}_Y \pi_Y^{Y,Y} \bar{N}_Y^2}{\Omega}, P_{YM} = \frac{(\bar{\theta}_Y + 1) \pi_M^{Y,M} \bar{N}_Y}{\Omega}, P_{YO} = \frac{(\bar{\theta}_Y + \bar{\theta}_O) \pi_O^{Y,O} \bar{N}_Y \bar{N}_O}{\Omega}, \\ P_{MM} &= \frac{\pi_M^{M,M}}{\Omega}, P_{OM} = \frac{(\bar{\theta}_O + 1) \pi_O^{O,M} \bar{N}_O}{\Omega}, \text{ and } P_{OO} = \frac{\bar{\theta}_O \pi_O^{O,O} \bar{N}_O^2}{\Omega},\end{aligned}\tag{3.15}$$

where

$$\begin{aligned}\Omega &= (\bar{\theta}_Y + 1) \pi_M^{Y,M} \bar{N}_Y + (\bar{\theta}_Y + \bar{\theta}_O) \pi_O^{Y,O} \bar{N}_Y \bar{N}_O + (\bar{\theta}_O + 1) \pi_O^{O,M} \bar{N}_O \\ &\quad + \bar{\theta}_Y \pi_Y^{Y,Y} \bar{N}_Y^2 + \pi_M^{M,M} + \bar{\theta}_O \pi_O^{O,O} \bar{N}_O^2.\end{aligned}\tag{3.16}$$

Even though it would appear that we could identify more than the four unknown parameters in this system of six equations (i.e., the individual θ_i s and N_i s), Levitt and Porter (2001) point out that these six equations are linearly dependent and so, in practice, only the four ratios $(\bar{\theta}_Y, \bar{\theta}_O, \bar{N}_Y, \bar{N}_O)$ can be separately identified.

Empirical Implementation

To estimate the parameters of this model with our data, we need an expression for the joint distribution of driver types involved in fatal accidents. This likelihood function is given by the multinomial distribution under the assumption that the composition of driver types in one fatal crash is independent of the composition of driver types in other fatal crashes. Letting A_{ij} represent the number of two-car fatal crashes involving driver types i and j , and A represent the total number of two-car fatal crashes, we can define this likelihood as follows:

$$\Pr(A_{YY}, A_{MM}, A_{OO}, A_{YM}, A_{OM}, A_{YO} | A) = \frac{(A_{YY} + A_{MM} + A_{OO} + A_{YM} + A_{OM} + A_{YO})!}{A_{YY}! A_{MM}! A_{OO}! A_{YM}! A_{OM}! A_{YO}!} P_{YY}^{A_{YY}} P_{MM}^{A_{MM}} P_{OO}^{A_{OO}} P_{YM}^{A_{YM}} P_{OM}^{A_{OM}} P_{YO}^{A_{YO}}. \quad (3.17)$$

Maximizing this likelihood with respect to each P_{ij} yields the intuitive solution:

$$\hat{P}_{ij} = \frac{A_{ij}}{A}. \quad (3.18)$$

The final step involves solving for $(\bar{\theta}_Y, \bar{\theta}_O, \bar{N}_Y, \bar{N}_O)$ using our estimated values for the P_{ij} s. This is accomplished by taking the following ratios and simplifying:

$$\frac{\hat{P}_{YM}^2}{\hat{P}_{YY}\hat{P}_{MM}} = \frac{A_{YM}^2}{A_{YY}A_{MM}} = R_Y = \left(2 + \bar{\theta}_Y + \frac{1}{\bar{\theta}_Y}\right) \left(\frac{(\pi_M^{Y,M})^2}{\pi_Y^{Y,Y} \pi_M^{M,M}}\right) \quad (3.19)$$

and

$$\frac{\hat{P}_{OM}^2}{\hat{P}_{OO}\hat{P}_{MM}} = \frac{A_{OM}^2}{A_{OO}A_{MM}} = R_O = \left(2 + \bar{\theta}_O + \frac{1}{\bar{\theta}_O}\right) \left(\frac{(\pi_M^{O,M})^2}{\pi_O^{O,O} \pi_M^{M,M}}\right). \quad (3.20)$$

These two quadratic equations can then be solved for $\bar{\theta}_Y$ and $\bar{\theta}_O$:

$$\bar{\theta}_Y^2 + \left(2 - \frac{R_Y}{\pi_{MY}}\right) \bar{\theta}_Y + 1 = 0 \quad \bar{\theta}_Y = \frac{\left(\frac{R_Y}{\pi_{MY}} - 2\right) \pm \sqrt{\left(\frac{R_Y}{\pi_{MY}}\right)^2 - 4 \frac{R_Y}{\pi_{MY}}}}{2}, \quad (3.21)$$

where

$$\frac{R_Y}{\pi_{MY}} = \frac{(\pi_M^{Y,M})^2}{\pi_Y^{Y,Y} \pi_M^{M,M}} \quad (3.22)$$

and

$$\bar{\theta}_O^2 + \left(2 - \frac{R_O}{\pi_{OM}}\right)\bar{\theta}_O + 1 = 0 \quad \bar{\theta}_O = \frac{\left(\frac{R_O}{\pi_{OM}} - 2\right) \pm \sqrt{\left(\frac{R_O}{\pi_{OM}}\right)^2 - 4\frac{R_O}{\pi_{OM}}}}{2}, \quad (3.23)$$

where

$$\frac{\pi_{OM}}{\pi_{OM}} = \frac{(\pi_O^{O,M})^2}{\pi_O^{O,O} \pi_M^{M,M}}. \quad (3.24)$$

These two equations are identical to those employed by Levitt and Porter (2001) except for the addition of the relative crash fatality rate terms, π_{MY} and π_{OM} , a point to which we will return later in this chapter.

For values of $\frac{R_i}{\pi_{ij}} \geq 4$, equations 3.20 and 3.21 produce at least two solutions for $\bar{\theta}_i$, one solution greater than or equal to one and one solution less than one. To choose one of the solutions, we must make an assumption about the relative riskiness of older and younger drivers. We assume that older and younger drivers are at least as likely to cause an accident as are middle-aged drivers and so choose values of $\bar{\theta}_i \geq 1$. The validity of this assumption rests on both a priori reasoning and empirical evidence (see the preceding section in this chapter).

For values of $\lambda_i < 4$, equations 3.20 and 3.21 produce nonreal value solutions for $\bar{\theta}_i$. These values of λ_i are inconsistent with the binomial distribution; no combination of $\bar{\theta}_i$ and \bar{N}_i can produce this outcome. However, when $\lambda_i < 4$, we can still generate the maximum likelihood estimates $\bar{\theta}_i$ and \bar{N}_i . They are, respectively, $\bar{\theta}_i = 1$ and $\bar{N}_i = \frac{A_i}{\hat{p}_{ij}}$.

Once we have $\bar{\theta}_Y$ and $\bar{\theta}_O$, we can form the ratio $\frac{\hat{p}_{ii}}{\hat{p}_{ij}}$ and solve for \bar{N}_i :

$$\begin{aligned} \bar{N}_Y &= \frac{(\bar{\theta}_Y + 1)\pi_M^{YM}}{\bar{\theta}_Y \pi_Y^{YY}} \frac{A_{YY}}{A_{YM}} \\ \bar{N}_O &= \frac{(\bar{\theta}_O + 1)\pi_O^{OM}}{2\bar{\theta}_O \pi_O^{OO}} \frac{A_{OO}}{A_{OM}}. \end{aligned} \quad (3.25)$$

The relative exposure is literally a measure of the relative crash opportunities of older and younger drivers. This means that exposure is not a measure of the relative number of miles driven *per older driver*; rather, it is a measure of the relative total miles driven. This is critical for the interpretation of the parameters; since the population of drivers 25–64 years old is much larger than that 65 and older, the relative exposure will tend to be less than 1, even if

older drivers drive much more than younger drivers. We discuss this further when we present our empirical results.

Estimating Relative Crash Fatality Rates

If we were to ignore the possibility that older drivers are likelier than younger drivers to die as a result of an accident, our estimates of θ_O would be biased upward. Accounting for differences in fatal crash rates requires estimates of the π_i^{jj} s. An estimate of π_i^{jj} is

$$\frac{F_i^{jj}}{A^{jj}}, \quad (3.26)$$

where F_i^{jj} is a count of the number of fatalities of type i that occur in accidents between drivers of type i and j and A^{jj} is the number of accidents between drivers of type i and j . We do not observe A^{jj} in our data. Instead, we observe the number of accidents between drivers of type i and j that result in a fatality, which clearly is a much smaller number than the number of all accidents between drivers of type i and j . Consequently, we can only estimate relative crash fatality rates, eliminating the need for data on accidents. For example,

$$\frac{\frac{F_Y^{YM}}{A^{YM}}}{\frac{F_M^{YM}}{A^{YM}}} = \frac{F_Y^{YM}}{F_M^{YM}} \quad \text{and} \quad \frac{\frac{F_O^{OM}}{A^{OM}}}{\frac{F_M^{OM}}{A^{OM}}} = \frac{F_O^{OM}}{F_M^{OM}}. \quad (3.27)$$

Thus, for example, our estimate of the relative crash fatality rate of individuals in the cars of younger drivers is just the ratio of the number of fatalities in cars of younger drivers in fatal accidents involving younger and middle-aged drivers (F_Y^{YM}) to the number of fatalities in cars of middle-aged drivers in fatal accidents involving younger and middle-aged drivers (F_M^{YM}). These ratios, however, are not enough because the relative crash fatality rates in equations 3.20 and 3.21 include additional terms:

$$\overline{\pi_{MY}} = \left(\frac{(\pi_M^{YM})^2}{\pi_Y^{YY} \pi_M^{MM}} \right) = \frac{\pi_M^{YM}}{\pi_M^{MM}} \frac{\pi_M^{YM}}{\pi_Y^{YY}} \quad \text{and} \quad \overline{\pi_{OM}} = \left(\frac{(\pi_O^{OM})^2}{\pi_O^{OO} \pi_M^{MM}} \right) = \frac{\pi_O^{OM}}{\pi_O^{OO}} \frac{\pi_O^{OM}}{\pi_M^{MM}}. \quad (3.28)$$

Our data do not permit computations of π_Y^{YY} , π_M^{MM} , and π_O^{OO} . Therefore, we make the simplifying assumption that the likelihood that someone in a middle-aged driver's car dies in an accident is the same whether that middle-aged driver crashes into another middle-aged driver or a younger driver ($\pi_M^{MM} = \pi_M^{YM}$). We make parallel assumptions for younger and older drivers ($\pi_Y^{YY} = \pi_Y^{YM}$, $\pi_O^{OO} = \pi_O^{OM}$, and $\pi_M^{MM} = \pi_M^{OM}$):

$$\begin{aligned}
\frac{\pi_{MY}}{\pi_Y} &= \left(\frac{(\pi_M^{YM})^2}{\pi_Y^{YY} \pi_M^{MM}} \right) = \frac{\pi_M^{YM} \pi_m^{YM}}{\pi_M^{MM} \pi_Y^{YY}} \cong 1 \times \frac{\pi_M^{YM}}{\pi_Y^{YM}} \frac{\pi_{OM}}{\pi_Y} \\
&= \left(\frac{(\pi_O^{OM})^2}{\pi_O^{OO} \pi_M^{MM}} \right) = \frac{\pi_O^{OM} \pi_O^{OM}}{\pi_O^{OO} \pi_M^{MM}} \cong 1 \times \frac{\pi_M^{OM}}{\pi_O^{OM}}.
\end{aligned} \tag{3.29}$$

Estimating Standard Errors

Levitt and Porter (2001) derive standard errors analytically using the Hessian matrix of the likelihood function. In our case, however, we do not estimate the full model using the likelihood function. In particular, we estimate the relative fatality rates separately and use these estimates to estimate the crash incidence and exposure rates. This complicates our ability to derive the standard errors analytically. To circumvent this problem, we adopt an empirically based bootstrapping procedure to estimate the standard errors. The bootstrapping procedure follows three steps. First, we resample observations at random with replacement.⁶ The resampling was conducted within equal mixing groups. Second, using the resampled data, we recalculated the relative crash fatality rates, crash incidence rates, and exposure rates for older and younger drivers. Finally, we repeated this procedure 100 times. Standard errors are computed for each parameter using the observed standard deviations in the bootstrap samples.

⁶ This resampling was implemented using the `bsample` command on Intercooled Stata® version 9.0 for Microsoft® Windows®.

The FARS Data and Our Sample

This chapter describes our data source (FARS), provides descriptive statistics on two-car crashes between younger and older drivers over the period of our data, and then describes how we disaggregate fatal accident counts in an effort to satisfy the equal mixing assumption discussed in Chapter Three.

The Fatal Accident Reporting System

We use FARS data to estimate the relative riskiness and exposure of older drivers. FARS records detailed information on all automobile accidents involving a fatality in the United States.¹ The FARS data, which have been collected annually since 1975, are derived from reports produced by state transportation agencies that collect information about fatal accidents from medical examiners, coroners, and emergency medical and police accident reports. The data are widely considered to represent a complete census of fatal automobile accidents in the United States. The last year of data used in this study is 2003.

The FARS data provide information on all persons involved in a fatal accident (e.g., age, sex, involvement, culpability, blood alcohol content, past driving record), details of the accident itself (e.g., time, location, road conditions, contributing factors), and information about the vehicles involved (e.g., make, model, safety equipment). The breadth of information captured in these data is of great use to us because it allows us to control not only for driver age but also for other factors (such as weather and time of day) that can contribute to an accident. Additionally, the large sample sizes in FARS allow us to estimate the items of interest with precision, even when we disaggregate the data into specific groups.

To fit with the empirical method outlined in the previous chapter, we restrict our analysis to crashes in which there are exactly two vehicles (and no pedestrians) involved. As noted in Chapter Three, we observe crashes in which one or more fatalities occurred in at least one of the two vehicles involved in the crash. We place no restrictions on the number of passengers in either car. We exclude a small number of crashes involving buses and motorcycles from the analysis. We also exclude drivers with a recorded age of less than 15 years.

¹ Detailed information about FARS can be found in Tessmer (2002).

Table 4.1 lists the sample sizes by year for two-car crashes that meet our sample selection criteria. The sample sizes are similar across years; there are between 10,000 and 13,000 fatal two-car crashes each year between 1975 and 2003. The total sample size—334,806 two-car crashes—is large; still, on average, we use less than half of all fatal crashes reported in FARS.

Table 4.1
Two-Car Fatal Crashes, 1975–2003

Year	Crashes
1975	11,021
1976	11,133
1977	11,992
1978	12,722
1979	12,726
1980	11,931
1981	11,876
1982	10,565
1983	10,385
1984	10,899
1985	11,120
1986	11,458
1987	11,967
1988	12,222
1989	12,212
1990	11,683
1991	10,837
1992	10,579
1993	11,085
1994	11,511
1995	11,616
1996	11,915
1997	12,132
1998	11,800
1999	11,690
2000	11,561
2001	11,428

Table 4.1—Continued

Year	Crashes
2002	11,444
2003	11,296
1975–2003	334,806

SOURCE: 1975–2003 FARS.

NOTE: Sample restricted to two-car fatal crashes in which no pedestrians, buses, motorcycles, or drivers less than 15 years of age were involved.

Defining Crash Types by Driver Age

We divide drivers into three groups defined by age: 15–24 (younger), 25–64 (middle-aged), and 65 and older (older). We define the younger group as 24 and younger, since age 24 is a standard threshold for insurance companies for the purposes of determining premiums. We chose age 65 and older to define the older group, since a large fraction of individuals retires at age 65 in the United States. In Chapter Five, we report results based on alternative age ranges.

Table 4.2 shows the distribution of two-car crashes by crash type. There are six possible combinations of driver types in two-car crashes: two younger drivers, a younger driver and a middle-aged driver, a younger driver and an older driver, two middle-aged drivers, a middle-aged driver and an older driver, and two older drivers. The single largest category of crashes involves one younger and one middle-aged driver, representing just under 32 percent of the sample. Crashes involving two older drivers are relatively rare, representing only 1.3 percent of the sample. The middle-aged group, which is the largest subset of the driving population, is involved in 85 percent of all two-car crashes. A younger driver is involved in about 45 percent of crashes and an older driver is involved in just over 23 percent of crashes.

Disaggregating Two-Car Crashes

To satisfy the assumption of equal mixing, we must disaggregate the data on two-car crashes into groups in which we believe older and younger drivers are reasonably likely to be equally mixed with one another. For example, the equal mixing assumption is not likely to hold if we were to look at all two-car crashes that occur in the United States on a given day. Older drivers are likelier to drive during the day and are likelier to live in Florida than in Alaska. The equal mixing assumption becomes increasingly plausible as we examine smaller periods of time and smaller geographic areas (e.g., during the day in Florida). Within such boundaries, at a particular point in time in a particular location, equal mixing is certainly satisfied.

Table 4.2
Fatal Two-Car Crashes, by Crash Type

Crash Type	Crashes	Percent of All Crashes
Young, young	25,218	7.53
Young, middle-aged	106,337	31.76
Young, older	20,273	6.06
Middle-aged, middle-aged	124,602	37.22
Middle-aged, older	53,970	16.12
Older, older	4,406	1.32
Total	334,806	100
Any younger driver	151,828	45.3
Any middle-aged driver	284,909	85.1
Any older driver	78,649	23.5

SOURCE: 1975–2003 FARS.

NOTE: Sample restricted to two-car fatal crashes as in Table 4.1.

Although we have a large sample of crashes in our data, we can only disaggregate our counts so far. The relatively small number of crashes between two older drivers is particularly limiting. Thus, we cannot, for example, disaggregate crashes by hour of day (as in Levitt and Porter [2001]). For example, in the entire time period between 1975 and 2003, we observe only 35 fatal two-car crashes between the hours of 11:00 p.m. and midnight involving two drivers ages 65 and older. About 96 percent of fatal two-car crashes involving two older drivers occur between 7:00 a.m. and 10:00 p.m., compared to 73 percent of all other two-car crashes.

We disaggregate fatal crashes into different groups based on various crash characteristics. At our highest level of disaggregation, we break the data into 6,120 potential groups according to time of day (three categories), days of the week (two categories), time of year (two categories), speed limit (two categories), state (51 categories), and year (five categories). The specific categories are as follows. The first category for time of day we call *rush hour*, which is between 8:00 and 10:00 a.m. and between 4:00 and 6:00 p.m. We call the hours between 10:00 a.m. and 4:00 p.m. *daytime* and the hours between 6:00 p.m. and 8:00 a.m. *nighttime*. These time-of-day categories account for the fact that older drivers drive most often during daytime hours. We divide days of the week into two categories, *weekend* and *weekday*, to account for the likelihood that traffic is lighter on weekend days. We divide time of year into *winter and fall* (October–March) and *spring and summer* (April–September) to account for variation in road conditions attributable to weather.

To allow for the possibility that drivers of different ages drive on roads with varying speed limits we divide our data into crashes occurring in speed zones of 45 mph or less and those occurring in speed zones of more than 45 mph. To account for differences in driver types across geographic areas, we divide our sample by state and by whether the crash occurred in an urban or rural setting. Finally, we allow for the possibility that crash types have varied

over time by dividing our crashes into five year groups: 1975–1979, 1980–1985, 1986–1991, 1992–1997, and 1998–2003.

Table 4.3 shows how accident characteristics vary by driver type. Specifically, the table reports the percent of crashes with a given characteristic for crashes involving a younger driver, a middle-aged driver, or an older driver. The table shows that older drivers are considerably less likely to drive during nighttime hours. More than 50 percent of fatal crashes involving a younger driver and about 44 percent of crashes involving a middle-aged driver take place during nighttime hours, while only 18 percent of crashes involving an older driver occur during nighttime hours. Conversely, older drivers are considerably likelier than younger and middle-aged drivers to drive during daytime hours. Only 23 percent and 26 percent of crashes involving a younger or a middle-aged driver, respectively, occur during daytime hours, whereas 43 percent of crashes involving older drivers occur during these hours.

Table 4.3
Crashes with Particular Accident Characteristics, by Driver Age

Accident Characteristic	Percentage of Crashes Involving		
	Younger Driver	Middle-Aged Driver	Older Driver
Time of day			
Rush hour	26.5	30.0	38.9
Daytime	22.5	26.4	43.3
Nighttime	51.1	43.7	17.9
Time of week			
Weekday	64.3	69.7	75.4
Weekend	35.7	30.4	24.6
Time of year			
Winter or fall	48.7	50.3	50.1
Spring or summer	51.3	49.7	49.9
Speed limit			
45 mph or less	35.3	32.6	38.8
Over 45 mph	64.7	67.4	61.2
Urban or rural			
Urban	38.2	36.6	39.4
Rural	61.8	63.4	60.6

SOURCE: 1975–2003 FARS.

NOTE: Sample restricted to two-car fatal crashes as in Table 4.1. Columns may not sum to 100 percent due to rounding.

Differences in the frequency of crashes involving all ages of drivers analyzed by other accident characteristics are less pronounced. Crashes involving older drivers are likelier to occur during weekdays, particularly relative to those involving younger drivers. Crashes are evenly split between spring and summer and winter and fall for all three age groups. There is also very little variation across groups in the fraction of crashes in urban and rural areas, with just over a third of crashes occurring in urban areas. Crashes involving older drivers are likelier to occur in slower speed zones; 39 percent of their crashes occur in speed zones of 45 mph or less, compared to 35 percent of crashes involving younger drivers.

The Relative Riskiness and Exposure of Older Drivers

Employing the model in Chapter Three, we report in this chapter that older drivers (65 and older) are about 16 percent likelier than middle-aged drivers (25–64 years old) to cause an accident. Our preferred estimates also indicate that older drivers drive far fewer miles than do middle-aged drivers (about 82 percent fewer miles). Both of these estimates are statistically significant at better than the 1-percent significance level. In Chapter Six, we discuss what these results imply about the need for additional policies aimed at reducing the risks posed by older drivers.

But first, we provide additional details surrounding our estimates of relative riskiness and exposure. In the first section of this chapter, we show, consistent with our empirical model, that our estimate of the relative riskiness of older drivers increases as we further disaggregate our data. Our preferred estimates of relative riskiness and exposure are those generated by the greatest level of disaggregation that our data can support.

In the next section, we compare our preferred estimates to the more naive estimates of relative riskiness and exposure presented in Chapter Two. We show that our estimate of relative riskiness is significantly less than that implied by the ratio of fatalities to vehicle miles driven. However, we also show that our estimate of relative riskiness is quite similar to that based on forming the ratio of auto accidents in general to vehicle miles driven.

The third section reports estimates of the relative crash fatality rate, which suggest that differences in fragility can account for why our estimate of relative riskiness is so much smaller than the estimate of relative riskiness based on the ratio of fatalities to vehicle miles driven. Our estimates imply that drivers and passengers riding in cars driven by older drivers are nearly seven times likelier to die in an auto accident than are passenger and drivers riding in cars driven by middle-aged drivers.

The fourth and fifth sections of this chapter show how our estimates of relative riskiness and exposure vary by driver's age and by accident circumstances. These estimates indicate that relative riskiness actually decreases slightly between 55 and 75 years old, while relative exposure falls sharply.

Main Results

Table 5.1 presents estimates of the relative riskiness and exposure of older and younger drivers (both defined relative to middle-aged drivers), by increasingly refined disaggregations of the data. The table illustrates the importance of disaggregation for satisfying the equal mixing assumption. Recall from Chapter Three that violations of the equal mixing assumption will lead to downwardly biased estimates of the relative riskiness of older drivers and upwardly biased estimates of the relative exposure of older drivers.¹

The first disaggregation level column of Table 5.1 shows the estimated relative riskiness and exposure of older ($\bar{\theta}_o$) and younger ($\bar{\theta}_y$) drivers in the entire sample (i.e., no disaggregation). The estimates of 1.0 imply that there is no difference in the relative riskiness of younger, middle-aged, and older drivers. However, the equal mixing assumption is almost certainly violated at this level of aggregation.

Table 5.1
The Relative Riskiness and Exposure of Older and Younger Drivers, by Increasing Levels of Disaggregation

Estimated Parameter	Level of Disaggregation			
	1	2	3	4
$\bar{\theta}_y$	1.00	1.23 (0.0019)	1.76 (0.0012)	2.88 (0.0011)
$\bar{\theta}_o$	1.00	1.07 (0.0011)	1.08 (0.0008)	1.16 (0.0010)
N_y	0.39	0.32 (0.0015)	0.29 (0.0007)	0.30 (0.0007)
N_o	0.08	0.07 (0.0003)	0.08 (0.0002)	0.12 (0.0002)
Type of disaggregation	All cases	Time of day, year, time of year, time of week, speed limit	Level 2 + urban or rural, fraction of population age 60+	Level 2 + state
Total number of groups	1	120	960	6,000
Groups with nonmissing data	1	118	700	1,635

SOURCE: 1975–2003 FARS.

NOTE: Sample is restricted to two-car crashes as in Table 4.1. Parameter estimates represent weighted averages across cells, where weights are the total number of older–older, middle-aged–middle-aged, and older–middle-aged driver crashes. Bootstrapped standard errors are in parentheses.

¹ This follows Levitt and Porter (2001), who demonstrate that the estimates of the relative riskiness of drunk drivers increase from 3.8 to 7.5 from the least to the most disaggregated grouping of their data.

In the second disaggregation level column of Table 5.1, we disaggregate by time of day, year, time of year, time of week, and speed limit. At this level of disaggregation, we estimate that older drivers are 7 percent likelier than middle-aged drivers to cause an accident ($\theta_o = 1.07$). Younger drivers are 23 percent likelier than middle-aged drivers to cause an accident ($\theta_y = 1.23$). We note here that the relative risk parameters are estimated separately within each group (i.e., there is a separate estimate of relative riskiness for each group defined by time of day, year, time of week, and speed limit). The table reports the weighted average across the relative riskiness parameters estimated within each group. The weights place more weight on groups that have greater numbers of observations.²

In the third disaggregation level column of Table 5.1, we disaggregate further by urban or rural and four groups based on the state-level fraction of the population that is 60 or older (based on 2000 census data [U.S. Census Bureau, 2001; see Appendix C]). We form these four groups by ranking states into quartiles based on the fraction of the population that is 60 or older in a given year (so a state may change quartiles over time). Most states have older populations that range between 10 and 20 percent of the total population. The percentages that delineate the quartiles are 14, 16, and 18 percent. The purpose of this particular disaggregation is to maintain larger sample sizes than we would obtain when we disaggregate by state (as in disaggregation level column 4), but still accounting for variation in the fraction of the population age 60 and above across states. This additional disaggregation increases the estimated relative riskiness of older drivers only slightly, from 1.07 to 1.08. However, the estimated relative riskiness of younger drivers increases substantially, from 1.23 to 1.76.

The fourth disaggregation level column of Table 5.1 reports our preferred estimates. Here, we disaggregate crashes by time of day, year, time of year, time of week, speed limit, and state.³ At this level of disaggregation, we estimate that older drivers are 16 percent likelier than middle-aged drivers to cause a two-car crash. Younger drivers are 2.88 times likelier to cause a two-car crash than are middle-aged drivers. These results imply that, although drivers 65 and older are likelier than middle-aged drivers to cause a two-car crash, they are far less likely than drivers 15–24 years old to cause a two-car crash.

Our estimates of relative exposure are not as sensitive to the level of disaggregation. The relative exposure of older drivers increases from 0.08 to 0.12 as the level of disaggregation increases. The relative exposure of younger drivers decreases from 0.39 to 0.29. Our preferred estimates in disaggregation level column 4 of Table 5.1 imply that both younger and older individuals drive much less than do middle-aged individuals. Older individuals account for only 12 percent as many miles as middle-aged people. Younger individuals account for about 30 percent as many miles as middle-aged drivers.

² The weights equal the total number of crashes in each cell involving two middle-aged drivers, two older drivers, or a middle-aged and an older driver. We use the total number of crashes involving older and middle-aged drivers because these are the crashes used to estimate the primary parameter of interest, the relative crash incidence rate for older drivers. An alternative weight would be to use the total number of all crashes in a cell. The total number of crashes and just crashes involving older and middle-aged drivers are highly positively correlated, however, so this choice has little impact on the results.

³ We also experimented with further disaggregating crashes by urban or rural, but the number of groups with missing data increased considerably and there was no significant change in our estimates of relative riskiness and exposure.

Of course, older and younger individuals are much less prevalent in the overall population of licensed drivers. To interpret these relative exposure estimates, it is then helpful to control for the population shares of the three groups in question. In 2000, younger, middle-aged, and older individuals accounted for approximately 14, 72, and 14 percent of the total population of licensed drivers, respectively. Thus, our estimate of relative exposure implies that the average younger individual drives about 154 percent as many miles as the average middle-aged driver does and that the average older driver drives about 62 percent as many miles as the average middle-aged driver does.

The table also includes standard errors for the estimates obtained using the bootstrap procedure described in Chapter Three. The estimates are very precise. Note that no standard errors were computed for the first column because there is no sampling error with this estimate (FARS represents the universe of all crashes). In the remaining columns, our estimates of the relative riskiness of older and younger drivers are always statistically different from 1 at the 1-percent confidence level or better.⁴ The relative exposure rates are also statistically different from their corresponding fractions of licensed drivers in the population. Because these standard errors are so small, we omit them from the following tables except in a few cases in which their magnitude is large enough to affect our inferences.

As we discussed in Chapter Four, our ability to disaggregate is limited by sample size. This fact is highlighted in the bottom two rows of Table 5.1, which reports the total possible number of groups and the actual number of groups for which we are able to estimate relative riskiness and exposure. The level of disaggregation in the second disaggregation level column of Table 5.1 results in 120 possible groups. We can estimate relative riskiness and exposure for 118 of these groups.⁵ We lose far more groups in disaggregation level column 3, in which we estimate relative riskiness and exposure for 700 out of 960 possible groups. In our preferred specification (reported in disaggregation level column 4), we estimate relative riskiness and exposure for 1,635 out of 6,000 possible groups.

The inability to estimate relative riskiness and exposure in all possible groups should not affect our results. The reason we cannot estimate relative riskiness and exposure in some groups is that we do not observe any crashes between two older drivers.⁶ Because the FARS data represent a census of fatal accidents, this suggests that the cells for which we fail to observe crashes between older drivers represent times or places in which there simply are not many older drivers on the road. If older drivers are not present on the road, then their relative risk is not defined in these cells.⁷ Finally, we note that the groups in which we cannot compute relative riskiness

⁴ This can be tested by subtracting 1 from the relative crash rates and checking that the difference is more than twice the standard error.

⁵ The number of possible groups is the product of the number of different categories in each group (e.g., in disaggregation level column 2, the number of possible groups is $3 \times 5 \times 2 \times 2 \times 2 = 120$).

⁶ We delete cells if we are unable to estimate any of the parameters of interest: the younger to middle-aged or older to middle-aged drivers' relative risk or relative exposure. This can occur if (1) there are no fatal crashes involving a given driver type or (2) if there are no fatal crashes in which someone in a given driver type's car was killed. The majority of missing cells are due to no crashes involving two older drivers.

⁷ We might care about the hypothetical relative riskiness that we would observe if older drivers did drive in these areas. For example, perhaps older individuals choose not to live in areas where driving is risky to them. In econometric terms, the

and exposure are groups that have relatively few crashes and so would receive relatively little weight in our overall averages regardless.

Comparison to Alternative Estimates

In Table 5.2, we compare these estimates (the Levitt-Porter estimates) of the relative riskiness and exposure of older and younger drivers to estimates we can derive from the descriptive data presented in Chapter Two. For relative riskiness, we compare the Levitt-Porter estimates to the relative number of fatalities and accidents per vehicle mile driven (F/M and A/M) and the relative number of fatalities per licensed driver (F/N). For relative exposure, we compare the Levitt-Porter estimates to the relative number of vehicle miles driven. The Levitt-Porter column of Table 5.2 reports estimates of relative riskiness and exposure using data from between 1998 and 2003. This sample restriction is made because our data on VMT and licensed drivers are from 2001.

The table shows that the estimates of relative riskiness based on fatalities per mile driven and fatalities per licensed driver are comparable to the Levitt-Porter estimates in the case of younger drivers. All three estimates imply that younger drivers are more than twice as likely as middle-aged drivers to cause an accident. However, the Levitt-Porter estimates of relative riskiness of older drivers are substantially lower than estimates based on fatalities per mile driven and substantially higher than estimates based on fatalities per licensed driver.

Table 5.2
Comparison of Relative Riskiness and Exposure Estimates

Parameter Estimate	Method				
	Levitt-Porter	F/M	A/M	F/N	VMT
θ_y	2.46	2.40	2.39	2.13	—
θ_o	1.17	2.10	1.19	0.88	—
N_y	0.24	—	—	—	0.36
N_o	0.12	—	—	—	0.11

NOTE: Levitt-Porter estimates are estimated as in disaggregation level column 4 of Table 5.1 but restricted to the years 1998–2003. F = number of fatal accidents involving driver of age i . N = number of licensed drivers. M = vehicle miles driven. A = number of accidents involving driver of age i . VMT is the ratio of older to middle-aged drivers' VMT and younger to middle-aged drivers' VMT.

hypothetical risk would be analogous to the average treatment effect of aging on accident risk if individuals were randomly assigned to cells, whereas the parameter we estimate is the local average treatment effect for those who drive.

This makes sense because fatalities per VMT will likely overestimate relative riskiness, since older drivers are likelier to die in accidents and because fatalities per licensed driver will likely underestimate relative riskiness, since older drivers drive so few miles compared with middle-aged drivers. The Levitt-Porter estimate, on the other hand, accounts for both miles driven and relative crash fatality rates. But note that the relative riskiness estimate based on accidents per VMT (A/M) is remarkably close to the Levitt-Porter estimate for both older and younger drivers. A/M is biased by neither the failure to account for VMT or relative crash fatality rates and provides some independent confirmation that the Levitt-Porter estimates are reasonable.

Finally, note that the Levitt-Porter estimate of relative exposure is close to that generated by simply comparing VMT across different ages of drivers. This is comforting, since, conceptually, VMT ratios correspond closely to the Levitt-Porter formulation of relative exposure.

Relative Crash Fatality Rates

The importance of accounting for relative crash fatality rates (e.g., $\overline{\pi_o}$) is evident in Table 5.3. The relative crash fatality rate column of the table reports our estimate of the relative crash fatality rate for older and younger drivers. These estimates imply that individuals (passengers or drivers) riding in a car driven by an older individual are 6.73 times likelier to be killed than are individuals riding in a car driven by a middle-aged driver. Individuals riding in a car driven by a younger individual are 1.44 times likelier to be killed than are individuals riding in a car driven by a middle-aged driver.⁸

The relative riskiness columns of Table 5.3 report the Levitt-Porter estimates of relative riskiness that do and do not account for differences in crash fatality rates. Not accounting for

Table 5.3
The Impact of Crash Fatality Rates on Estimates of Relative Riskiness

Age Group	Relative Crash Fatality Rate $\left(\overline{\pi_i}\right)$	Relative Riskiness $\left(\overline{\theta_i}\right)$	
		Unadjusted	Adjusted
Older drivers	6.73	6.26	1.16
Younger drivers	1.44	3.35	2.88

SOURCE: 1975–2003 FARS.

NOTE: Unadjusted relative riskiness is calculated as if the relative crash fatality rate were equal to 1. Adjusted relative riskiness accounts for relative crash fatality rates. Sample is restricted to two-car crashes as in Table 4.1. Parameter estimates represent weighted averages across groups, where weights are the total number of older–older, middle-aged–middle-aged, and older–middle-aged drivers' crashes. Groups are defined as in disaggregation level column 4 of Table 5.1.

⁸ If we look only at two-car crashes in which there were no passengers, we find that younger drivers are approximately equally likely as middle-aged drivers to be killed in an accident. Older drivers are about 1.5 times likelier than middle-aged drivers to be killed.

crash fatality rates, we find that the estimated relative riskiness of older drivers is 6.26, an estimate that is much higher than the estimate of 1.16 we obtain when we do account for relative crash fatality rates. The relative riskiness of younger drivers is also overestimated when we fail to account for relative crash fatality rates (3.35 versus 2.88).⁹

Estimates of Relative Riskiness at Even Older Ages

In Table 5.4, we show how our estimate of older drivers' relative riskiness changes as we increase the threshold age defining *older* in our data from 55 years old to 70 years old. In so doing, we also, by necessity, redefine the *middle-aged* group. Thus, the change in relative riskiness with the age threshold is attributable to changes in the absolute riskiness of both the older and reference populations. Because the number of groups for which we can estimate relative riskiness declines as we increase the age threshold, Table 5.4 uses only those groups for which we can compute relative riskiness when we define our older group as 70 and older.

In the first and second parameter estimate columns of Table 5.4, we see, as expected, that the relative crash fatality rate increases and relative exposure decreases as we increase the age threshold. However, somewhat unexpectedly, we see in the third parameter estimate column of Table 5.4 that relative riskiness declines as we increase the age threshold. This implies that the very oldest drivers are less likely than the only moderately older drivers to cause a crash. A potential explanation for this finding is that the population of drivers becomes increasingly select with age. Only the healthiest and safest older drivers remain on the road at very old ages.

Table 5.4
Relative Crash Fatality Rate, Exposure, and Riskiness of Older Drivers, by Age

Age Threshold	Parameter Estimate			A/M (2000)
	π_o	N_o	θ_o	
55	4.35	0.23	1.18	—
60	5.43	0.15	1.14	1.08
65	6.68	0.11	1.13	1.19
70	8.26	0.08	1.09	1.43

SOURCE: 1975–2003 FARS.

NOTE: Sample is restricted to two-car crashes as in Table 4.1. Parameter estimates represent weighted averages across groups, where weights are the total number of older–older, middle-aged–middle-aged, and older–middle-aged drivers' crashes. Groups are defined as in disaggregation level column 4 of Table 5.1 but restricted to those used to estimate parameters when the age threshold is 70. A/M is defined as in Figure 2.2.

⁹ Note that these results suggest that the relatively low estimate of relative riskiness for older drivers of 1.16 is not simply due to potential violations of the equal mixing assumption. Clearly, accounting for relative crash fatality rates is what drives our estimate of relative riskiness downward substantially.

Alternatively, it could be that drivers become increasingly cautious and defensive as they age, so much so that they actually become safer drivers as they reach more advanced ages.

This latter finding is contrary to that implied by estimates of relative riskiness based on accidents per VMT (fourth parameter estimate column of Table 5.4). That estimate of relative riskiness increases with the age threshold. One possible reason for this is that, if the likelihood of injury increases with age, the likelihood that an accident is reported in GES (which, remember, is a sample of police-reported accidents) could be increasing with the age of drivers involved in the accident. If so, this would impart an upward bias to estimates of relative riskiness based on accidents per VMT.

How the Relative Riskiness and Exposure of Older Drivers Varies by Accident Characteristics

Our main results imply that older drivers are somewhat likelier to cause a crash than are middle-aged drivers but drive many fewer miles. In this section, we explore how relative riskiness and exposure vary with accident characteristics, such as time of day, time of year, and speed limit. For example, older drivers might find it more difficult to drive at night because of vision problems. This could cause older drivers to drive less during those hours and, perhaps, be riskier drivers when they do.

In Table 5.5, we examine how relative riskiness and exposure of older and younger drivers varies by time of day. Because older drivers tend to avoid the nighttime hours, we limit this analysis to the hours between 7:00 a.m. and 9:00 p.m. We exclude any crashes in which FARS indicates that alcohol was a contributing factor and further restrict the sample to crashes occurring Monday through Friday in areas with speed limits between 25 and 60 mph from March through October. We estimate relative riskiness and exposure for each hour of the day within states. The table reports weighted averages of these estimates, with the weights defined as before.

The first two parameter estimate columns of Table 5.5 report relative riskiness and exposure of older drivers. There is no clear pattern in relative riskiness by time of day. The relative riskiness of older drivers is somewhat higher between 7:00 and 10:00 a.m., ranging from 1.15 to 1.51. Relative riskiness is then somewhat lower between 10:00 a.m. and 2:00 p.m. After 2:00 p.m., it increases again and stays relatively high until 7:00 p.m. Between 7:00 and 9:00 p.m., the estimates imply that older and middle-aged drivers are equally risky. Thus, although the pattern is somewhat inconsistent, it appears that older drivers are slightly more dangerous during rush hour periods and less dangerous during off-peak hours.

A more obvious pattern by time of day is evident in the relative exposure of older drivers. Relative exposure is at its lowest between 7:00 and 9:00 a.m. It then increases during the off-peak daytime hours, particularly between 10:00 a.m. and noon. Relative exposure then declines during the rush hour period and stays below 0.10 between 4:00 and 9:00 p.m.

The second two parameter estimate columns of Table 5.5 report the relative riskiness and exposure of younger drivers by time of day. Younger drivers are relatively risky throughout the day, without any consistent pattern of rising or falling risk (though there does appear to

Table 5.5
Relative Riskiness and Exposure, by Time of Day

Hour	Parameter Estimate			
	θ_o	N_o	θ_y	N_y
7:00 a.m.	1.18 (0.013)	0.06 (0.001)	2.03 (0.034)	0.23 (0.002)
8:00 a.m.	1.15 (0.011)	0.09 (0.001)	3.05 (0.093)	0.22 (0.004)
9:00 a.m.	1.51 (0.038)	0.11 (0.001)	4.17 (0.098)	0.18 (0.003)
10:00 a.m.	1.12 (0.009)	0.13 (0.001)	2.82 (0.045)	0.27 (0.004)
11:00 a.m.	1.04 (0.004)	0.13 (0.001)	2.54 (0.058)	0.20 (0.002)
12:00 p.m.	1.01 (0.001)	0.10 (0.001)	2.02 (0.039)	0.24 (0.002)
1:00 p.m.	1.02 (0.002)	0.12 (0.001)	4.29 (0.138)	0.23 (0.003)
2:00 p.m.	1.81 (0.043)	0.10 (0.001)	2.04 (0.037)	0.26 (0.002)
3:00 p.m.	1.24 (0.024)	0.10 (0.001)	1.76 (0.030)	0.26 (0.002)
4:00 p.m.	1.17 (0.010)	0.07 (0.001)	3.09 (0.042)	0.20 (0.002)
5:00 p.m.	1.26 (0.013)	0.08 (0.001)	2.14 (0.037)	0.33 (0.003)
6:00 p.m.	1.22 (0.025)	0.08 (0.001)	1.92 (0.043)	0.40 (0.005)
7:00 p.m.	1.00	0.10 (0.002)	4.03 (0.141)	0.35 (0.006)
8:00 p.m.	1.00	0.09 (0.002)	1.18 (0.014)	0.49 (0.007)

SOURCE: 1975–2003 FARS.

NOTE: Sample is restricted to two-car crashes as in Table 4.1 and further restricted to those crashes in which there was no reported alcohol involvement that occurred between 7:00 a.m. and 9:00 p.m., March through October, Monday through Friday, in areas with a speed limit between 25 mph and 60 mph. Parameter estimates represent weighted averages across state and hour-of-day groups, where weights are the total number of older-older, middle-aged–middle-aged, and older–middle-aged drivers' crashes. Bootstrapped standard errors are represented in parentheses.

be a slight peak at 9:00 a.m.). The relative exposure of younger drivers fluctuates throughout the daytime hours, without any clear pattern. We begin to see a sharp increase in the relative exposure of younger drivers in the nighttime hours, rising to 0.49 at 8:00 p.m. Interestingly,

when the relative exposure is at its peak, the relative riskiness of younger drivers is at its lowest point, just 1.18.

Table 5.5 also presents standard errors for the estimates. As before, all coefficients are precisely estimated. All relative risk ratios (other than those equal to one) are significantly different from 1 and, in most cases, will be different from those in different hours of the day. Likewise, the relative exposure rates are also significantly different across hours in most cases.

We implement a regression to explore how relative riskiness and exposure vary across all the groups in our data. The regression has the following specification:

$$\begin{aligned} \overline{\theta}_{ijt} = & \alpha_0 + \alpha_1 \text{daytime}_i + \alpha_2 \text{weekend}_i + \alpha_3 \text{season}_i + \alpha_4 \text{speed}_i \\ & + \text{state}_j \alpha_5 + \text{year}_t \alpha_6 + \varepsilon_{ijt}, \end{aligned} \quad (5.1)$$

where $\overline{\theta}_{ijt}$ is the relative riskiness of older drivers in group i in state j at time t ; *daytime*, *weekend*, *season*, *speed*, *state*, and *year* are defined as in Chapter Four. ε_{ijt} is a random error term. The unit of observation in this model is one of 1,635 groups (as in disaggregation level column 4 of Table 5.1). The model then allows us to isolate the main effect of each group characteristic while holding all other group characteristics constant. We estimate an analogous model in which the dependent variable is the relative exposure of older drivers.¹⁰

Table 5.6 reports the average relative riskiness and relative exposure for each group as implied by the estimated regression coefficients.¹¹ Examining the hour-of-day panel of Table 5.6, we see that the relative riskiness of older drivers is higher during rush hour than during off-peak and nighttime hours. The difference in relative riskiness between off-peak and rush hour is not statistically significant. The estimates also imply that older drivers are significantly less likely to drive during rush hour.

In the time-of-week panel of Table 5.6, we see that the relative riskiness of older drivers is slightly lower on weekends, but the difference between weekday and weekend relative riskiness is not statistically significant. There is a large difference in the relative exposure of older drivers between weekdays and weekends. Relative exposure is nearly twice as high on weekends as on weekdays. This difference is statistically significant.

Table 5.6 also shows that the relative riskiness of older drivers is slightly less in the winter and fall than in the summer and spring (1.29 versus 1.33). This difference is not statistically

¹⁰ Note that the dependent variable in this model is an estimate, meaning that it has an error term. However, as long as the error in the left variable is uncorrelated with the exogenous independent variables, it is “absorbed” by the error term in an ordinary least squares (OLS) regression and requires no special adjustment (Greene, 2003, p. 84).

¹¹ The base predicted value in this model is the constant in the regression equation. The following categories represent the omitted category in the regressions: *daytime*: *off-peak*, *weekday*, *spring and summer*, *speed limit over 45 mph*. The omitted category for the year variables is the 1975 to 1979 group. Technically, there is no omitted state; the constant we use is the average of the state fixed effects (as done automatically by Stata’s *areg* command). Thus, the constant for each regression can be thought of as the average relative risk or relative exposure for off-peak daytime hours, during the week, during the spring and summer months, in speed zones of over 45 mph, from 1975 to 1979. The predicted values for the other categories represent the sum of this constant plus the estimated coefficient for that category.

Table 5.6
Relative Risk and Exposure of Older Drivers, by Accident Characteristics

Accident Characteristic	θ_o	N_o
Hour of day		
Daytime: rush hour	1.29	0.09
Daytime: off-peak	1.22	0.11 ^a
Nighttime	1.03 ^a	0.12 ^a
Time of week		
Weekday	1.29	0.09
Weekend	1.27	0.17 ^a
Time of year		
Winter and fall	1.29	0.09
Spring and summer	1.33	0.11
Speed limit		
Over 45 mph	1.29	0.09
45 mph or less	1.16 ^a	0.13 ^a
Years		
1975 to 1979	1.29	0.09
1980 to 1985	1.15	0.09
1986 to 1991	1.35	0.07 ^a
1992 to 1997	1.22	0.07 ^a
1998 to 2003	1.27	0.07 ^a

SOURCE: 1975–2003 FARS.

NOTE: Average value of parameters within accident categories are estimated from the regression specified in equation 5.1. Each cell in the table is equal to the regression constant plus the estimated coefficient for the specified category.

^a Statistically significant at the 1-percent level.

significant. There is a slight decrease in the relative exposure of older drivers in the winter and fall, but, again, the difference is not statistically significant.

Table 5.6 also compares the relative riskiness and exposure of older drivers when driving in slower and faster speed zones. These results suggest that older drivers are likelier to cause a crash in faster speed zones than in slower speed zones. The estimated relative riskiness is 1.29 in speed zones of 45 mph and higher, compared to 1.16 in speed zones under 45 mph. We also see that older drivers are likelier to avoid faster speed zones, with a relative exposure rate of 0.13 in the slower speed zones compared to 0.09 in the faster speed zones. Both of these differences are statistically significant.

Finally, the table displays how relative riskiness and exposure have changed over time in our sample. We can see that, across the different time periods, there is no clear trend in the riskiness of older drivers, and none of the differences is statistically significant. On the other hand, there does appear to be a slight decline in exposure for older drivers in the later years. It is not a clear trend, however. It simply appears that exposure of older drivers declined somewhat in the late 1980s.

Conclusions

This research has employed an innovative statistical procedure to estimate the relative riskiness and exposure of older drivers using data on counts of two-car accidents involving drivers of different ages. Our principal estimates imply that drivers 65 and older are 16 percent likelier than drivers 25–64 years old to cause an accident (see Table 5.1, disaggregation level column 4).

Our estimate of the relative riskiness of older drivers is considerably lower than what is implied by a comparison of fatalities per VMT between older and middle-aged drivers. Such an estimate implies that older drivers are more than twice as likely as middle-aged drivers to cause an accident. Although our research cannot definitively conclude why our estimate of the relative riskiness of older drivers is so much lower than one based on the ratio of fatalities to VMT, we suspect that it is because our estimate accounts for the much higher fragility of older drivers. By our estimates, drivers and passengers riding in cars driven by older drivers are nearly seven times likelier to die in an auto accident than are passengers and drivers riding in cars driven by middle-aged drivers. Since the age of passengers and drivers is highly positively correlated, this statistic suggests that older individuals are much likelier than middle-aged individuals to die in a car accident.

The increase in fragility with age is also evident in Table 6.1, which reports, by age, the probability that a driver or passenger who is involved in a car crash with two or more cars will be killed or otherwise injured. The increase in the probability of being killed in a fatal accident increases with age for both drivers and passengers. Interestingly, the probability of experiencing an injury in accidents in general does not increase as sharply with age, which suggests that relatively minor crashes impact young and old alike but that more severe accidents are likelier to harm older individuals than they are to harm younger individuals. One implication of this finding is that the ratio of accidents in general to VMT is likely to facilitate a much better estimate of the relative riskiness of older drivers than is the ratio of fatalities to VMT. Indeed, our estimate of relative riskiness is quite close to that based on the ratio of accidents to VMT (see Table 5.3).

It seems likely that the sharp increase in fragility with age can account at least partly for the sharp decrease in exposure with age. Our estimate of the relative exposure of older drivers implies that older drivers drive only 62 percent as much as do middle-aged drivers, on average. Exposure also appears to decline generally with age, even at advanced ages (in our results and using survey data), so there is at least a raw, negative correlation between fragility and the amount that individuals choose to drive.

Table 6.1
Fatality and Injury Rates, by Age

Age	Fatality Rate (fatal accidents)			Injury Rate (all accidents)		
	Driver	Passenger	Both	Driver	Passenger	Both
0–19	0.36	0.19	0.24	0.16	0.18	0.17
20–29	0.33	0.24	0.30	0.18	0.24	0.19
30–49	0.31	0.25	0.30	0.17	0.27	0.19
50–59	0.36	0.30	0.35	0.19	0.30	0.20
60–69	0.44	0.36	0.42	0.18	0.30	0.20
70–79	0.59	0.51	0.57	0.20	0.33	0.22
80+	0.68	0.33	0.51	0.18	0.08	0.12

NOTES: Sample includes drivers and passengers in multiple-car accidents only. Fatality rates in fatal accidents are computed from the 2000–2001 FARS. Injury rates in all accidents are computed from the 2000–2001 GES. Injury rates are weighted using weights provided by GES.

That older drivers are only 16 percent likelier to cause a two-car crash than are middle-aged drivers might come as a surprise to some readers, especially given the attention this subject has received in the media in recent years and the reasonable assumption that driving ability should worsen as mental and physical conditions deteriorate. But it is important to recognize that our estimates reflect the riskiness of older drivers who continue to drive. We suspect that the riskiest older drivers significantly limit how much they drive or choose not to drive at all so as to lower the risk that they might cause property damage or injure themselves or others. This conjecture is supported by our finding that our estimate of relative riskiness actually falls as we increase the age threshold defining “older” drivers from 55 years old to 70 years old. An explanation for this pattern in relative riskiness is that self-regulation becomes increasingly effective with age. Only the healthiest and safest drivers continue to drive at more advanced ages.

An alternative to the self-regulation hypothesis is that state licensing regulations have succeeded in identifying the riskiest older drivers and discouraging them from driving.¹ That is, in the absence of state licensing regulations, such as mandatory vision and road tests, accelerated and in-person renewal policies, and mandatory physician reporting of medical conditions to state licensing authorities, the relative riskiness of older drivers would be considerably higher.

However, this hypothesis is not supported by existing empirical evidence. Evidence on the effect of licensing requirements on the accident rate of older drivers is limited and focused on vision testing. A number of studies have found that states requiring vision tests for older drivers lower fatal accident rates of older drivers (Levy, Vernick, and Howard, 1995; Shipp, 1999; Nelson, Sacks, and Chorba, 1992). Shipp (1999), for example, reports that the fatality rate is 12 percent less among older drivers in states that require vision tests to obtain a driver’s license than in states that do not. Grabowski, Campbell, and Morrissey (2004) do not find any

¹ Experience rating by auto insurance companies might also play an important role in causing the riskiest older drivers to curtail their driving.

evidence that vision testing affects the number of older driver fatalities, but do find evidence that in-person license renewals lower fatality rates among the oldest drivers (85 and older). Our estimates indicate that the relative riskiness of older drivers changed little between the early 1970s and the last period of our data, 1998–2003 (see Table 5.4), a time during which many states adopted more-stringent licensing requirements for older drivers. Given that most studies find little or no correlation between state licensing policies and the riskiness of older drivers, it seems likely that self-regulation plays a far more important role than licensing policies in reducing the riskiness of older drivers.

As the U.S. population ages, the number of injuries, especially fatal ones, sustained by older individuals in automobile accidents will surely rise. However, this research concludes that this increase in injuries will occur not so much because older individuals are that much likelier to cause an accident, but primarily because their likelihood of injury is so high when they are involved in an accident.

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