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DECISIONS?

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Working Paper 20679  
<http://www.nber.org/papers/w20679>

NATIONAL BUREAU OF ECONOMIC RESEARCH  
1050 Massachusetts Avenue  
Cambridge, MA 02138  
November 2014

This paper was funded in part by a grant from the National Institute on Alcohol Abuse and Alcoholism (NIAAA, #R01AA017913-01A1). The sponsor had no role in the design or conduct of this study. There are no conflicts of interest nor any financial disclosures for any of the authors. We also thank Hanming Fang, University of Pennsylvania, and Ahmed Khwaja, Yale University, for their collaboration in writing the proposal that led to the grant, and for assistance in developing the questionnaire used in this study. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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# Does Private Information Influence Automobile Insurance Purchase Decisions?

Frank A. Sloan, Patricia A. Robinson, and Lindsey M. Eldred

NBER Working Paper No. 20679

November 2014

JEL No. D82,I12,R41

## **ABSTRACT**

This study quantifies the importance of private information, separates the extent to which the positive correlation between the accident probability and insurance coverage reflects adverse selection and moral hazard, and analyzes market segmentation on objective accident risk. We use data we collected to examine the importance of potential sources of private information in individuals third- and first-party insurance choices. Individuals with higher subjective accident probabilities have less liability exposure post insurance purchase and more often experience an accident, conditional on factors insurers use for risk classification. This evidence is consistent with the positive correlation between accident occurrence and liability insurance coverage. We find that the positive correlation almost completely reflects adverse selection. In analysis of insurer sorting, we find that accident-free drivers obtain coverage from insurers with higher independent agency quality ratings. High-quality insurers eschew low-quality drivers on measured dimensions because these drivers are more likely to possess private information about their driving ability and proclivities that affect expected loss. Drivers with a higher risk on factors observable to insurers tend to have private information about their accident risk. This sorting process reflects an institutional response to asymmetric information, and assures a continuous supply of private insurance to unsafe drivers.

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## **I. Introduction**

Adverse selection and moral hazard plague all types of insurance markets in varying degrees. An additional anomaly of insurance markets is the important role of underwriting. Rather than take all potential customers by setting premiums that cover expected losses, insurers routinely reject applications from some potential customers. Various government interventions designed to protect consumers have affected private insurance markets, including rules pertaining to underwriting and premium-setting and mandatory insurance purchase requirements. At least some of these interventions in combination with adverse selection and moral hazard might be expected to discourage provision of certain types of coverage as well as institutional responses by suppliers of insurance.

Private information held by consumers is the source of adverse selection and moral hazard. In the case of adverse selection, consumers possess some private information about the probability of loss that is unknown to the insurer when insurance is purchased. In contrast, moral hazard arises because having insurance causes behavioral changes of insureds not easily observable by insurers. In the context of automobile insurance, adverse selection and moral hazard occur when consumers possess an extensive amount of private information about their accident risk, *ex ante*, i.e., before the insurance purchase for adverse selection, and drive with less care conditional on the insurance purchase for moral hazard. In some cases, observable information is, for practical purposes, “private” since private insurers are not allowed by statute or regulation to use the information on accident risk in premium setting.

This study of the U.S. automobile insurance markets in four states, North Carolina, Pennsylvania, Washington, and Wisconsin, has three objectives: (1) to quantify the importance of private information; (2) to explain the positive correlation between the extent of insurance

coverage and ex post accident risk by quantifying moral hazard and hence to separate the extent of adverse selection from moral hazard; and (3) to analyze the practice of segmenting the market into good versus bad drivers as a response to private information and state restriction. Market segmentation may be an efficient mechanism for supplying insurance in a market in which consumers differ in terms of observable and unobservable accident risk.

Empirical studies of insurance purchase decisions have demonstrated that consumers possess private information when deciding whether to, and what insurance contract to purchase, and importantly, their private information comes in multi-dimensional forms. This information potentially comes from such sources as private information about risk types, as highlighted in classical models of insurance markets (Rothchild and Stiglitz 1976), but also in preferences, e.g., risk aversion, thrill seeking, tastes for goods that may encourage risk taking such as alcohol, and in subjective beliefs about the adverse consequences of risky behaviors. Also individuals may differ in cognitive ability, which affects their knowledge of the law and adverse consequences of risky behaviors, and, in the context of driving and automobile insurance, in their altruism toward other drivers and in driving skills, which in turn may affect choice of insurance contract and the amount of exposure to financial risk the individual bears when driving.

Even though recent literature has made substantial progress toward understanding the role of some types of private information, e.g., risk aversion, empirical analysis of sources of private information available to consumers in making insurance purchasing decisions has relied on data obtained from secondary sources. General-purpose surveys have sometimes included a few questions about private information relevant to insurance choices. By contrast, this study uses data collected specifically for our research. The data can be used to examine the importance of a wide variety of potential sources of private information simultaneously in

individuals' choices of third-party and first-party insurance policies.

We show that individuals with higher subjective probabilities of an accident have less liability exposure—the objective of liability insurance being to reduce such exposure, and are more likely to experience an accident ex post, conditional on factors used by insurers in risk classification. This evidence is consistent with a positive correlation between accident occurrence and liability insurance. We also show that individuals' self-rating of driving ability and subjective probability of reckless driving are important determinants of the individual's subjective probability of an accident.

We use these underlying dimensions of private information about accident risk to measure moral hazard. In particular, we take advantage of survey questions that elicit how individuals' subjective probabilities of reckless driving change in response to changes in financial penalties from having a traffic violation, which is analogous to having different levels of financial exposure to an accident. We use relationships previously established in this study between subjective probabilities of reckless driving and subjective probabilities of an accident and between subjective probability of an accident and ex post accident risk in combination with our findings on responses to financial penalties to quantify moral hazard and thus separate adverse selection from moral hazard.

Finally, we investigate sorting of drivers among insurers based on drivers' accident risk. We observe a pattern that accident-free drivers select insurers, which are higher quality in terms of ratings by independent agencies. Conceptually, there are two types of drivers, those with a clean driving record during the past three years and those with prior accidents or violations during this look-back period. Some insurers may eschew the risky type because these drivers are likely to have private information about their driving abilities and proclivities that affect the

future probability of a loss. This sorting process, which leads to some insurers specializing in provision of coverage to high risk/high loss variance drivers, reflects an institutional response to asymmetric information and assures a continuous supply of private insurance to unsafe drivers.

This study makes several contributions to research on the role of private information and its consequences for how insurance markets function. First, our results extend our understanding of how subjective beliefs are formed, namely that: individuals' beliefs about the probabilities of engaging in reckless driving behaviors in the future are directly related to their subjective beliefs about experiencing an accident in the same future time period: and subjective beliefs about the probability of an accident are reflected in the extent to which people are exposed to loss from accidents after purchasing insurance and in subsequent realizations of accidents. Second, individuals are able to gauge in quantitative terms the extent to which reckless driving will result in higher insurance premiums, which implies that experience-rated premiums can deter reckless driving. Third, using our survey data, we implement a method for quantifying moral hazard, which allows us to separate adverse selection from moral hazard. Our method for quantifying the extent of moral hazard does not rely on the assumption of negative state dependence. Fourth, we examine sorting by insurers according to the objective risk of an accident in an insurance market with mandatory minimum levels of insurance coverage and discuss why such sorting occurs as a response to adverse selection. To our knowledge, ours is the second study to investigate how insurer underwriting policies reflect insurers' priors about private information, and the first study to do this for an insurance market in which insurance coverage is mandatory.

The organization of the remaining sections is as follows: Section II describes institutional features of the U.S. automobile insurance market. Section III describes basic features of the

survey we conducted for this study. Section IV focuses on the role of private information in the automobile insurance market—particularly the relationships between individuals’ subjective probabilities of being involved in an automobile accident in the next year and various other dimensions of private information, insurance contract choice, and ex post accident risk. In Section V, we use information from hypothetical scenarios posed in our survey to assess the extent of moral hazard. In Section VI, we investigate the relationship between observable and unobservable accident risk and various measures of insurer quality. Section VII discusses implications of our findings and study conclusions.

## **II. Background on Automobile Insurance Markets**

Government intervention in the automobile insurance markets reflects financial externalities of such insurance (e.g., absent insurance, accident victims may not be able to recover their losses), perceived consumer ignorance of the attributes of insurance policies, and the widespread notion that driving is a right, particularly since driving is often essential for employment and performing various household duties. Financial externalities have led to mandatory insurance coverage. Consumer ignorance has led to review of policy forms to assure that the terms of the contract of understandable to consumers. The notion of driving as a right has been a factor in premium regulation, community rating, take all comers, guaranteed renewability of policies, and formation of public high-risk pools. There is some segmentation of the market by risk class as reflected by the presence of private surplus line insurers in some states, i.e., insurers specializing in insuring the highest-risk drivers.

In the U.S., mandatory liability insurance coverage is nearly universal if one includes financial responsibility laws, which require that the individual be able to demonstrate the financial ability to cover the loss in the event of an accident, as a weak form of mandatory

coverage. Every state, except for New Hampshire, requires that drivers offer proof of financial responsibility.<sup>2</sup> All other states mandate financial responsibility, and most states require it be in the form of a minimum level of liability insurance that covers personal injury and property damages to a third-party if they cause an accident. Of our four study states, North Carolina, Pennsylvania, and Washington offer some drivers other options to satisfy financial responsibility including a choice between liability insurance, self-insurance, proof of assets over a specified amount, an uninsured motorist fee, or a cash or surety bond deposited with the state, but liability insurance is often the most practical option for drivers.<sup>3</sup> The requirement that drivers purchase minimum amounts of liability insurance prevents unraveling of contracts offering such minimum coverage, which has occurred in other insurance markets, e.g., health insurance (Cutler and Reber 1998).

In addition to mandatory insurance, there are many types of optional automobile insurance coverage, including collision insurance which covers property damage to the policyholder's own vehicle in the event of an accident. We focus on liability insurance, which typically has no deductible, and secondarily on first-party collision insurance, which is typically subject to a deductible.

Even though most drivers are, in effect, required to carry liability insurance, some insurers may not insure high-risk drivers. Often the stated reason is that they do not have claims

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<sup>2</sup> N.H. Stat. Rev. Ann. § 264.2. New Hampshire requires drivers to obtain liability insurance in the case of a conviction for motor vehicle law violations, but does not require insurance before a conviction occurs. Among the four study states, Wisconsin did not mandate liability insurance coverage prior to June 1, 2010. As of this date the state requires minimum liability coverage.<sup>2</sup> Previously, drivers were not required to obtain liability insurance or prove financial responsibility in order to register their vehicles. Our data on insurance coverage are for after this statutory change was implemented.

<sup>3</sup> NC Gen. Stat. § 20-309 (2013); 17 Pa.C.S. § 1782 (2013); Wash. Rev. Code. Ann. § 46.30; § 46.29.550, 46.29.630, 46.29.090, (2013). This option, for most drivers, is not feasible as it frequently requires a large cash deposit or bond; beyond the reach of the average driver. Furthermore, even though it is authorized by statute, not all states present this as an option to all consumers and interested drivers must meet certain specifications and work directly with the state to set up financial responsibility other than liability insurance.



experience to assess the risk of such drivers. In three of the four states, all except North Carolina, insurers can refuse to write coverage.

There are four ways states deal with the underwriting issue that some persons may not be able to secure “affordable” coverage and hence be unable to drive legally: a high-risk pool; an assigned-risk system; a state-run reinsurance facility; or a state-funded plan. Of the study states, only North Carolina has a reinsurance facility.<sup>4</sup> All insurers selling automobile insurance in the state must take part, and as a result, an insurer may choose to insure a high-risk driver under its regular plan or transfer it to the reinsurance facility.<sup>5</sup> In contrast, Pennsylvania, Washington, and Wisconsin utilize an assigned risk plan. These plans also require all automobile insurers to participate.<sup>6</sup> The state assigned risk plans are run by a state-created office governed by a board of insurance companies licensed in the state. However, unlike a reinsurance facility, assigned risk plans do not offer choice of insurer.

Automobile insurers commonly use experience rating to increase or decrease premiums according to recent driving history (Lemaire 1995). Some states regulate experience rating with a statewide point system. Of our study states, North Carolina mandates insurance increases with a state-created system. Moving violations, including at-fault accidents, speeding tickets, and Driving While Intoxicated (DWI) convictions, are assigned points and the number of points on your driving record determines the premium surcharge.<sup>7</sup> The other study states regulate

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<sup>4</sup> NC Gen. Stat. § 58-37-1 (2013)

<sup>5</sup> Although empirical support is lacking, the underlying rationale is that such reinsurance gives drivers the ability to a free choice of insurance carrier. It also means that individuals do not know when they are insured under the reinsurance facility as the individual’s insurance contract is issued by the (primary) insurer.

<sup>6</sup> 75 Pa.C.S. § 1741 (2013); Wash. Rev. Code. Ann. § (2013); Wis. Stat. § 632.35 (2013); Wis. Admin. Code Ins § 6.54 (2013).

<sup>7</sup> For example, in North Carolina a driver with an otherwise clean record who is at-fault for an accident causing less than \$1,800 of property damage will get one point added to his driving record resulting in a mandatory thirty percent premium increase.

surcharges but do not require specific schedules.<sup>8</sup>

Insurance applications require basic demographic information including location, age, gender, race, and marital status. However, in some states, these are protected categories and companies are not allowed to set premiums without proper justification. The rules vary across our study states.<sup>9</sup> In all study states, premiums may reflect accident risk in the location in which insurance is sold. The statutes are silent regarding insurer requests for information on driving characteristics, such as annual mileage, vehicle specifications or use. The driving record of an insured driver may be a significant source of information on driving risk for an insurer. Insurance companies in the United States can purchase an individual's three-year driving record—including convictions, violations, and related activity recorded by the department of motor vehicles—for a nominal fee.

Insurers rarely if ever request some types of private information insureds are likely to possess because it is impossible to verify statements made by potential or actual insureds from independent sources, e.g., on risk preferences, use of intoxicating substances, and quality of driving. Insurers might ask about specific chronic conditions known to affect accident risk such as alcohol use disorder, epilepsy, or narcolepsy. Such information can be verified from medical records or health insurance claims.

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<sup>8</sup> In Pennsylvania, drivers cannot be surcharged or non-renewed if the claim resulting from an accident in the preceding three years if the insurance company is reimbursed for at least 60 percent of the total amount of the paid claim (Pennsylvania Insurance Department 2013). Wisconsin requires surcharges be applied uniformly and are required to be filed with the Office of the Commission of Insurance (Office of the Commissioner of Insurance 2011)

<sup>9</sup> North Carolina prohibits risk classification based on age and gender although insurers are allowed to impose a surcharge for drivers with less than three years driving experience. NC Gen. Stat. § 58-36-10 (2013). Pennsylvania prohibits unfair discriminatory underwriting (underwriting not backed by empirical evidence) based on race, religion, nationality, age, sex, family size, occupation, place of residence, or marital status. 40 P.S. § 1171.5(7)(iii) (2010). In contrast, Washington prohibits refusal of insurance or limits on benefits payable based on gender, marital status, or sexual orientation, but allows these factors to be used when “bona fide statistical differences in risk or exposure have been substantiated.” Wash. Rev. Code. Ann. § 48.30.300 (2013). Similarly, like Pennsylvania, Wisconsin prohibits denying benefits or refusing coverage based on sex, age, marital status, sexual preferences, location, race, or religion; however, the state does allow rate setting based on these characteristics, so long as there is credible supporting information. Wis. Stat. § 632.35 (2013); Wis. Admin. Code Ins § 6.54 (2013).

### III. Data

Battelle Memorial Institute conducted a three-wave survey of drinkers and drivers on our behalf in eight cities in four states during 2010-12, called the Survey of Alcohol and Driving (SAD). When possible, the questionnaire design was guided by questions included in prior surveys, albeit not all asked in the same survey. This study relies on data from all three waves.<sup>10</sup> The first wave, administered by telephone, included questions on: demographic characteristics/income/wealth; alcohol consumption; accident/traffic violation history; and altruism. The second wave, administered by computer about a month after wave 1, elicited information for which visual displays are helpful and/or questions involved detailed scenarios which would be challenging to pose orally (e.g., for eliciting risk preferences, willingness to pay to avoid paralysis from an automobile accident), and details about the respondent's automobile insurance policy. The third wave, also administered by computer, was conducted about a year after wave 1.<sup>11</sup>

Since the primary focus of the study was on drinking and driving, eligibility for the SAD required respondents to have driven and to have consumed alcohol during the last month, residence within one of eight study cities, and be age 18+. The eight cities were: Raleigh and Hickory, North Carolina; Philadelphia and Wilkes-Barre, Pennsylvania; Seattle and Yakima, Washington; and Milwaukee and La Crosse, Wisconsin. These represent a broad geographic spread of large and small cities. While eight cities are not representative of the U.S., the four study states in which the cities are located vary in alcohol consumption, rates of DWI, arrest

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<sup>10</sup> Although the SAD began before June 2010, information on insurance policies respondents had was obtained after this date.

<sup>11</sup> Survey instruments for the SAD can be found at (<http://dialog.econ.duke.edu/dapstudy>).

rates, criminal laws pertaining to DWI, demographic composition, and insurance law and regulation.<sup>12</sup>

The mean age of the study participants is 43.8. Mean educational attainment is 15.6 years, implying that on average, respondents nearly had a college degree, which is substantially above the U.S. average. Mean household income is \$81,470, also above average. Over half of sample is female (54.6%); 13.1 percent are non-white, and 46.6 percent are married. The participant recruitment process was designed to oversample persons who consumed large amounts of alcohol in order to study DWI decision-making and behaviors of such individuals in detail.

#### **IV. Private Information and Insurance Contract Choice**

##### **A. Overview**

We first assess the role of private information (1) in individuals' choices of automobile insurance coverage and hence their maximum exposure to loss, (2) in their accident risks, and (3) in the correlation between the two. An institutional feature of tort law in the U.S. is that when the defendant's liability obligation exceeds the person's wealth, the defendant is considered to be judgment proof (Shavell 2005). Our null hypothesis is that individuals in our sample who purchase very complete insurance and have no financial exposure from automobile accidents are

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<sup>12</sup> Per capita consumption of ethanol in gallons in 2007—NC (2.0), PA (2.2), WA (2.4), and WI (3.0) (National Institute on Alcohol Abuse and Alcoholism 2009). Arrest to population ratios varied from 0.25 percent (WA) to 0.67 percent (WI) in 2009 (our calculation from arrest data we obtained from each state). The four large cities—Seattle, Philadelphia, Raleigh, and Milwaukee—have populations 380,000-1.4 million. The smaller cities—Yakima, Hickory, Wilkes-Barre, and La Crosse—have populations 37,000-82,800. The racial makeup of each city varies, e.g., Philadelphia and Milwaukee with large African-American populations, 43 and 37 percent, respectively, Yakima with a large Hispanic population, 34 percent. Further, auto insurance varies greatly among the cities. According to (Smith and Wright 1992) in an article entitled “Why is Automobile Insurance in Philadelphia So Damn Expensive,” automobile liability insurance premiums in Philadelphia were about twice as high as they were in Seattle. Seattle's were about 50 percent higher than those in Milwaukee. Raleigh/Durham did not make the list. The authors attributed high premiums in some cities, at least in part, to large numbers of uninsured motorists in some markets. Ratios of uninsured motorist to bodily injury claims varied from 0.38 in Philadelphia, 0.14 in Milwaukee, to 0.089 for Seattle.

no more likely than others to report having an accident after purchasing their insurance. For example, a person with a net worth of \$1 million but with 100/300 (lower limit maximum insurer payment per person for bodily injury and upper limit maximum total insurer payment per accident, in thousands of dollars) would face a maximum liability exposure of \$700,000.

Like Finkelstein and McGarry (2006), we divide sources of information into three categories: (1) information insurers use in risk classification and hence in premium-setting; (2) information insurers are likely to elicit from consumers but which is not specifically used in risk classification; and (3) multiple sources of private information not available to insurers. We examine private information in multiple domains--the financial domain and driving domain, altruism toward others on the road, and subjective beliefs about the probability the person will engage in reckless driving in the next year—speeding or drinking and driving—to determine which types of private information can explain subjective beliefs about the probability of having an accident in the next year, observed insurance purchases, and ex post accident rates.

## **B. Three Types of Information**

### **B.1. Objective Factors Used by Insurers in Premium Setting**

Accident determinants used by insurers for risk classification fall into these general categories: demographic characteristics; driving attributes; driving history; and city. In our analysis of objective factors, demographic characteristics are: male under age 25; female under 25; and currently married. For driving attributes, we include binary variables for whether the person reported driving 15,000+ miles per year and type of primary vehicle—sedan, sport car, SUV, minivan, truck, or other—whether the person reports driving to work, driving a motor vehicle regularly as part of a job, and primary vehicle age. Driving history includes the number of: citations for speeding; arrests for DWI; and accidents during the past three years.

We use a linear probability model to determine the relationship between accident risk and information used by the insurer for risk classification. We estimate the following equation

$$Prob(Accident_{t-1} = 1 | X_{t-1}) = F(X_{t-1}' \beta) \quad (1),$$

where *Accident* is a binary variable for whether the person was involved in an accident in the past three years, and *X* is a vector of characteristics used by the insurer for risk classification. The dependent variable takes three alternative forms: (1) any accident; (2) any chargeable accident—a person is deemed responsible; and (3) any non-chargeable accident—a person is involved but not deemed responsible for causing the accident.

Table 1 reports the results of estimating eq. (1) for the three variants of the dependent variable. Young drivers, male and female, those who drive 15,000+ miles/year, and/or have prior speeding citations and DWI arrests have higher probabilities of an accident in the follow-up year. Persons currently married, drive a sports car, and residents of Yakima have a lower probability of an accident. Since most persons with accidents had non-chargeable accidents, results for the probability of having a non-chargeable accident are quite similar to those for the probability of having any accident.

We use the results from Table 1, col. 2, to calculate the predicted probability of an accident for each individual and include this predicted probability measure in subsequent analyses to account for information about accident risk known to the insurer.

## **B.2. Attributes Observed by Insurers but Not Used in Premium Setting**

Attributes observed by insurers but not used in risk classification are household income, educational attainment in years, and race/ethnicity.

## **B.3. Multiple Dimensions of Private Information**

In conceptualizing types of private information we consider these dimensions: driving skills and precaution levels; risk preferences; cognitive ability; impulsivity; depression; altruism; and maximum willingness-to-pay to avoid injury and disability. Each of these dimensions of private information was measured by the SAD.

Insurers know about the person's prior accident and arrest records, but the individual may know more about his or her quality of driving and precaution levels than is reflected in the person's driving history. To measure self-rated driving skills, the SAD asked respondents to rate their driving ability relative to others—worse, about the same, better, or much better. To measure precaution levels, the SAD elicited at baseline the individual's subjective probabilities of speeding 15 miles per hour or more over the speed limit and of driving at least once after having too much to drink in the next year. The SAD elicited, a year later, actual incidents of speeding and drinking and driving episodes during follow-up.

Risk preferences in the financial and driving domains may affect risk-taking in driving situations as well as demand for insurance. The SAD used the same measure of financial risk tolerance as the Health and Retirement Study (HRS). Following the HRS, SAD posed a hypothetical scenario to gauge the respondent's financial risk tolerance. The questions posed a gamble between a 50 percent probability of doubling lifetime income if the person wins the gamble and a 50 percent probability, alternatively, of losing half, one third, or one tenth of lifetime family income. The SAD elicited a more detailed measure of risk tolerance than the HRS. Based on the responses, we group respondents into three mutually exclusive categories: (1) least risk tolerant—respondents who rejected a gamble involving a 50/50 chance of doubling income or reducing income by 10 percent; (2) moderately risk tolerant—accepted gamble when odds are doubling income and losing anywhere from 10 to 50 percent of income; and (3) most

risk tolerant—accepted gamble involving doubling income versus losing all income (risk neutral to risk lover) or accepted a gamble involving loss of all income versus increasing income by 67 to 100 percent (risk lover).

Barsky et al. (1997) showed that this measure is positively associated with various dimensions of risk taking outside the financial domain. The authors did not compare responses to the HRS's questions on financial risk tolerance to driving risk-taking. While financial risk preferences are assumed to generalize to various decision-making contexts, some empirical evidence raises a question of the validity of assuming context-invariant risk preferences (Barseghyan et al. 2011; Einav et al. 2012). A utility function over wealth may relate much more directly to demand for insurance coverage than to risk-taking as a driver since reckless driving may be enjoyable to some drivers. If so, risk-takers in the financial domain may eschew insurance coverage for this reason, but they may demand insurance coverage because they realize that they have a higher probability of an accident because they are risk takers as drivers.

To measure risk tolerance in the driving domain, the SAD described the following scenario: “Imagine that you have to go to an important business meeting. There are heavy police patrols on the road you are traveling. You are a little tight in time to get to the meeting. If you do not speed, you are certain to be late by 10 minutes. If you speed 15 miles an hour over the speed limit, you can get there on time if you are not caught by the police. There is a 10% chance that you will be caught by the police and you will be sure to be late for the meeting by 30 minutes. Assume that the police only would give you a warning in this case, so that you would pay no fine or incur premium increases. Would you: (1) not speed and be late for your meeting; (2) speed less than 10 mph and be late less than 10 minutes; (3) speed 15 mph and take chances on being caught?”



Cognitive ability may affect the individual's ability to weigh potential benefits and costs of specific choices (Fang et al. 2008) and/or accuracy of a person's subjective beliefs.<sup>13</sup> The SAD included several measures for cognition, each based on questions from the HRS. To measure recall, the SAD incorporated an exercise in counting backwards to assess attention and processing speed, and an object naming test to assess language, and recall of the date and name of the Vice President of the United States and the Governor of the state in which the respondent resided. Second, to measure working memory, the SAD included a serial 7 subtraction test based on a sequence of 5 questions, starting with  $100 - 7$ , with the next question based on the respondent's answer to the first question  $-7$ , and so on. The maximum (best) score on this variable is 5. Third, the SAD measured the respondent's numeracy. The numeracy question sought to learn whether or not the respondent was able to make percentage calculations.

Impulsivity is a general term describing a tendency to act on a whim, hence disregarding a more thought-out rational long-term strategy for maximizing personal welfare (Madden and Johnson 2010). An impulsive individual may not consider future consequences of present actions and hence be more accident-prone. In psychology, impulsivity is an aspect of personality. In the context of subjective beliefs about having an accident, an individual who is impulsive may recognize that she is likely to act on a whim in the future, thus exposing her to a higher probability of personal harm (Frank A. Sloan et al. 2013). A parallel is the sophisticate in the literature on self-control versus the naïf who lacks self-control but is not able to incorporate lack of future self-control in making current decisions (Gruber and Köszegi 2001).

To measure impulsivity, the SAD incorporated impulsivity questions developed by Loewenstein et al. (2001). To conserve interview time, the SAD used an abbreviated version of

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<sup>13</sup> Evidence on the relationship between cognitive ability and accuracy of risk assessment from the SAD is mixed. See Frank A. Sloan et al. (2013).

the Loewenstein et al. scale. In the SAD, respondents were asked at wave 1 to respond on a 5-point scale to 12 statements designed to measure impulsivity. The scale ranged from strongly agree with the statement to strongly disagree. The statements to which respondents were to respond were: “1. I do things on impulse that I later regret; 2. I act on impulse; 3. I finish what I start; 4. I often do things on the spur of the moment; 5. I plan for the future; 6. I always consider the consequences before I take action; 7. I control my angry feelings; 8. There are so many little jobs that need to be done that I sometimes just ignore them all; 9. I fly off the handle; 10. I never seem to be able to get organized; 11. I rarely make hasty decisions; and 12. I am not a worrier.”

By leading to a feeling of hopelessness, depression may increase subjective beliefs about probabilities of adverse events occurring (Hepburn et al. 2009). To the extent that depression increases subjective probabilities of an accident arising from careless driving, it may increase the individual’s precaution level. However, it may also lessen the individual’s belief that the individual can control one’s fate, which may have the opposite effect. The SAD measured depression with questions from the SIG-E-CAPS, a screener for depression (Guck et al. 2003; Lieberman 2003), a screening tool widely used in clinical practice (Wise and Rundell 1994). SIG-E-CAPS contains questions about sleep problems (S), loss of interest (I), guilt, worthlessness, hopelessness, and regret (G), lack of energy, fatigue (E), reduced cognition or difficulty with concentration (C), appetite—either increased or decreased (A), psychomotor retardation (lethargy) or agitation (anxiety) (P), and suicidality (S). In total, the SAD included nine symptoms, the eight just listed plus depressed mood. The SAD asked survey participants to respond affirmatively if the person had a symptom during any full two-week period during the last 12 months. Our depression measure is a count of these symptoms.

Persons who are more altruistic, especially concerned about harming strangers, may be safer drivers and hence less accident-prone.<sup>14</sup> The SAD made statements relative to altruism toward non-family members, none of which reference alcohol consumption or DWI. Nine of the statements dealt with altruism without referring to family members. *Cet. par.*, we expect persons who are less selfish toward non-family members, i.e., internalize the externalities involving harm to others without incentives, to be less likely to drink and drive. The statements that did not refer to family members were: “1. I am hurt if what I do isn’t recognized; 2. I help so I can live with myself; 3. I am resentful when I do things for others; 4. people think I am selfish; 5. people think I am cold; 6. I’m not known for generosity; 7. I try to be thoughtful; 8. I think of myself as charitable; and 9. I go out of my way to help others.” Response options were: 1. “agree;” 2. “neutral;” and 3. “disagree.” The SAD phrased the statements so that some imply altruism while others imply selfishness. This was done to encourage respondents to read and consider each item.

Persons who place a lower value on avoiding injury and/or disability should be more prone to take risks that increase the probability of personal injury, including automobile accidents. The SAD included a set of questions designed to value the non-pecuniary loss from an automobile accident resulting in permanent paralysis. The question design sought to avoid common pitfalls in contingent valuation research and was based on questions one of us has used in previous surveys of willingness to avoid multiple sclerosis, a disability, and smoking-related diseases (Frank A. Sloan et al. 1998; Perreira and Sloan 2002; Khwaja et al. 2009). Respondents were asked to compare two areas: Area A which has the same monthly cost of living as the place where the respondent currently lives and is assumed to have a 0.01 probability of a person

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<sup>14</sup> There is little empirical evidence on this relationship. Using the same measure of altruism from SAD as in this paper, Frank A. Sloan and Eldred (2013) found that more altruistic persons toward strangers were less likely to drink and drive. In a study of adolescent driving behavior, Ulleberg and Rundmo (2003) found that more altruistic persons were more likely to exhibit positive attitudes toward safe driving.

getting into a automobile accident per year that results in the person becoming paralyzed. Area B has a \$X per month higher cost of living per year and a 0.008 probability of being involved in an automobile accident resulting in the person being paralyzed. To avoid starting point bias, the starting values for \$X were randomly assigned. Based on several rounds of questions, a final value for willingness to pay to avoid a 0.002 probability of being paralyzed from an automobile accident was assigned. The final value is the amount a person would pay per month in return for a reduced probability of paralysis of 0.002 per year.

To examine the relationship between the subjective probability of an accident in the following year and specific sources of private information, conditional on objective information used and not used by insurers, we estimate:

$$Subj. Prob. Accident_{t-1} = \beta_0 + \beta_1 Private Info_{t-1} + \beta_2 X_{t-1} + \varepsilon_{t-1} \quad (2),$$

where *Private Info.* is a vector of individual characteristics and beliefs not observed by the insurer. *X*, objective factors used in risk classification, and *Z*, factors observed by insurers but not used in risk classification.

Judging from the mean values of the covariates, most respondents think they are better than average drivers (Table 2, col. 1). The majority are moderately financially risk tolerant. Only a few respondents are most financially risk tolerant. On driving risk tolerance, most respondents also fall into the moderate category. However, almost a quarter of sample persons are most risk tolerant, higher than for financial risk tolerance. Forty-five percent believe that they would speed in excess of 15 miles per hour during the next year. By contrast, the subjective probability of drinking and driving in the next year is 0.17 for the analysis sample as a whole. The objective probability of an accident is 0.21.

Self-rating of driving ability is monotonically related to the subjective probability of an accident—people who believe they are worse drivers than others have a 0.10 higher subjective probability of an accident relative to those who believe they are much better drivers than others (col. 2). As one’s self-rated driving ability improves, the subjective probability of an accident during the following year falls.

Subjective probabilities of speeding and drinking and driving are positively related to the subjective probability of an accident. A one percentage point increase in the subjective probability of speeding or drinking and driving is associated with a 0.03 percentage point increase in the subjective probability of an accident.

More impulsive persons attach a lower probability of being involved in an accident in the next year, possibly because they underestimate the probability of taking impulsive actions in the foreseeable future. Higher income individuals had lower subjective probabilities of being in an accident, possibly because they intended to be more careful drivers, given they would be less likely to be judgment proof in the event of an accident. We find no evidence that risk tolerance, cognition, depression, altruism, and willingness-to-pay to avoid paralysis from an accident affect subjective beliefs about accident risk.

## **C. Choice of Insurance Coverage**

### **C.1. Financial Exposure to Liability from an Automobile Accident**

The SAD asked whether the person had liability insurance, and if so, what the liability limits were. The liability limits represent a measure of the quantity of liability insurance purchased, but the ultimate objective of such insurance is to protect the consumer against the financial risk from an automobile accident, which in turn depends on the individual’s wealth.

To measure the individual's maximum financial exposure to loss from an automobile accident, we subtract the higher liability limit from the person's household net worth with zero as the lower bound on exposure. For individuals without liability insurance, this is simply equal to the maximum of zero and net worth. Higher liability exposure corresponds to less complete insurance coverage. We estimate the following relationship:

$$Exposure_{t-1} = \beta_0 + \beta_1 Subj. Prob. Accident_{t-1} + \beta_2 X_{t-1} + \varepsilon_{t-1} \quad (3).$$

The coefficient of interest is  $\beta_1$ , which measures the effect of an individual's subjective probability of being involved in an accident during the following year on the maximum financial exposure to an automobile accident, given the individual's level of insurance coverage. For  $X$ , we use the predicted objective probability of an accident in the following year (from eq. 1). The classic model of uni-dimensional asymmetric information about risk type implies that  $\beta_1 < 0$ —an individual with a higher subjective probability of an accident will choose more complete insurance, or lower maximum liability exposure.

We find a statistically significant negative relationship between the subjective probability of an accident and level of liability exposure conditional on the objective predicted probability of an accident (Table 3, col. 5). Each additional 0.01 increase in the subjective probability of an accident in the following year leads to a \$4,207 decrease in maximum loss exposure. The parameter estimate on the objective probability is positive but statistically insignificant, reflecting higher premiums for higher objective accident risk, and possibly sorting on objective risk, as discussed below. We perform the same test on only those individuals who have liability insurance and obtain similar result (col. 6). The marginal effect of a 0.01 increase in the subjective probability is slightly higher in absolute value than before -\$4,574.

## **C.2. Demand for Collision Insurance**

Substituting binary variables to measure the individual's collision coverage, we estimate determinants of collision coverage. The relationship between the subjective probability of an accident and having collision insurance is also consistent with the classic prediction because the first dependent variable is defined for no collision coverage, but the parameter estimate is imprecisely estimated (col. 7). When the dependent variable is 1 for persons with collision insurance with a deductible exceeding \$500/year, neither parameter estimate on the subjective probability of an accident nor its objective counterpart are statistically significant at conventional levels (col. 8).

#### **D. Private Information and Ex Post Accident Risk**

##### **D.1. Relationship between Ex Ante Beliefs about Accident Probability and Ex Post Accident Risk**

The results in Table 3 show that the subjective accident probability affects individuals' choices about liability exposure. The importance of this finding depends on the degree to which individuals' subjective accident probabilities predict ex post accident risk. We explore this relationship next.

To investigate whether the subjective probability of an accident also affects individual accident risk, conditional on the insurer's classification of the consumer's accident risk, we estimate:

$$Accident_t = \beta_0 + \beta_1 Subj. Prob. Accident_{t-1} + \beta_2 X_{t-1} + \varepsilon_t \quad (4).$$

The dependent variable is a binary variable for whether the person had an accident in the year after the SAD elicited the subjective probability of an accident. The parameter of interest is  $\beta_1$ , which relates the subjective probability of an accident to actual accident occurrence. If individuals' subjective probabilities are accurate,  $\beta_1 = 1$ . If individuals' subjective probabilities

are unrelated to individuals' objective probabilities of an accident,  $\beta_1 = 0$ . If, in general, people can, but have difficulties forming subjective probabilities,  $0 < \beta_1 < 1$ .

Although the parameter estimates on the subjective probability of any accident during follow-up are positive, the parameter estimates have large associated standard errors (Table 4, cols. 1 and 2). The parameter estimate on the predicted objective probability of an accident is 0.30 and is statistically significant at better than the 0.01 level (col. 2). In an alternative specification with the total number of accidents, the number of chargeable, and the number of non-chargeable accidents as the dependent variables (cols. 3-8), the parameter estimates on the subjective probability of an accident in the following year are uniformly positive and statistically significant at conventional levels for the number of accidents (cols. 3-4) and the number of chargeable accidents (cols. 5-6). The corresponding parameter estimates on the subjective probability in the analysis of number of non-chargeable accidents are about of the same magnitude as for chargeable accidents but not statistically significant. The predicted probability of an accident, however, while positive in the analysis of all three dependent variables, is not statistically significant in the analysis of number of chargeable accidents, possibly reflecting a lack of statistical power. Taken in combination with the result showing that people with a higher subjective probability of an accident buy more complete liability insurance, these results imply adverse selection.

It remains possible that there are other dimensions of private information not captured by the subjective probability of an accident in the following year, e.g., unmeasured dimensions of risk and time preferences related to insurance coverage. For this reason, and to compare our results with those from previous studies, we perform two additional statistical tests.

## **D.2. Positive Correlation Tests**



Most previous studies of asymmetric information in insurance markets have focused on adverse selection. However, some recent empirical studies have found evidence of favorable selection (Fang et al. 2008). Favorable selection might arise in automobile insurance markets if persons who are not risk averse in the financial domain tend to be more careless drivers, thereby increasing the probability of an accident. Thus, depending on their previous driving records, persons who are not risk averse in the financial domain may be more likely to purchase complete automobile insurance coverage. Or favorable and adverse selection may offset each other.<sup>15</sup>

We perform two versions of the correlation test. First, we estimate a linear probability model of accident occurrence as a function of insurance coverage, controlling for risk classification, similar to Finkelstein and Poterba (2004):

$$Prob(Accident_t = 1 | X_{t-1}, CInsurance_{t-1}) = F(\beta_1 X_{t-1} + \beta_2 CInsurance_{t-1}) \quad (5),$$

where *CInsurance* is a vector of insurance coverage characteristics. With asymmetric information about risk type,  $\beta_2 > 0$ .

The parameter estimate on the binary variable for zero exposure is positive and statistically significant. (Table 5, Panel A). Fully insured are 0.047 more likely to have an accident in the following year (col. 2) than are individuals with above \$225,000 maximum loss exposure. Even after conditioning on insurer risk classification, fully insured individuals are 0.044 more likely to have an accident (col. 3). Therefore, we reject the null hypothesis of symmetric or offsetting dimensions of private information in liability insurance. The parameter

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<sup>15</sup> In addition, the literature, e.g., Finkelstein and Poterba (2004), has shown that asymmetric information may manifest itself in ways other than the positive correlation property. Aspects of insurance contracts chosen by the individual may reveal their private information. In FP's analysis, such a dimension was a minimum payment from the annuity irrespective of longevity ("guaranteed payment"). In our study's context, insurers may differ in both underwriting policy and, except for North Carolina, in the extent to which violations and accidents are experience-rated. Thus, a person with a clean driving record but with private information that she has a relatively high probability of a violation and/or accident may be unlikely to purchase insurance from an insurer with strict underwriting and experience-rating policies.

estimates on level of the collision insurance deductible are very imprecisely estimated. Results, not shown, using number of accidents as a dependent variable, are very similar to those reported in Panel A. Thus, the main takeaway is persons with complete insurance have a higher accident probability in the following year.

Second, we employ a procedure suggested by Chiappori and Salanie (2000)—that is, we estimate two equations with bivariate probit:

$$Prob(Accident_t = 1 | X) = F(\beta_1 X_{t-1}) \quad (6a)$$

$$Prob(Zero\ exposure_{t-1} = 1 | X) = F(\delta_1 X_{t-1}) \quad (6b),$$

where *Zero Exposure* is a binary variable set to 1 if the individual has zero liability exposure, i.e., complete liability insurance coverage. We measure the correlation,  $\rho$ , between the error terms of these two equations. With asymmetric information about risk type, there should be a positive correlation between the residuals of these two equations—i.e.,  $\rho > 0$ .

The correlation is positive and statistically significant, 0.15 based on data from the whole sample, and 0.14 when we condition on persons with liability insurance, which further supports our finding that people with more complete liability insurance coverage—i.e., with less exposure to financial risk following an accident—are more likely to be involved in an accident during the follow-up year (Panel B). This positive correlation between completeness of insurance coverage and ex post accident risk may reflect both adverse selection and moral hazard. In the next section we disentangle these two phenomena.

## **V. Separating Adverse Selection from Moral Hazard**

### **A. Overview**

Abbring et al. (2003) used panel data from insurance companies to distinguish between adverse selection and moral hazard based on negative state dependence. In the absence of moral

hazard, an individual's probability of getting involved in an accident this year should be independent of whether or not the person was involved in an accident last year. With moral hazard, however, and experience-rated premiums, having an accident in the previous year should lead to higher levels of precaution and a lower probability of an accident this year. This implies that a finding of negative state dependence can be taken as evidence of moral hazard.<sup>16</sup>

We do not use this approach for two reasons: (1) our panel consists of only two periods and (2) the probability of a chargeable accident in a year is low, providing in combination with our sample size, little statistical power to reject the null hypothesis of no negative state dependence. Fortunately, responses to a set of questions posed as hypotheticals in our survey allow us to employ an alternative approach for quantifying moral hazard and hence to parse effects of moral hazard and adverse selection.

Our approach involves several steps (Fig. 1). We describe our method for estimating each step below.

### **B. Step 1. Relationship between Expected Premium Increases and Reckless Driving**

The penalty from reckless driving was measured in the SAD by the change in the expected premium after speeding 15+ miles per hour over the posted speed limit, which reflects the probability of being pulled over and convicted for speeding by this amount of the limit, both elicited by the SAD. Given this expected premium increase, the SAD asked respondents to estimate the (subjective) probability of speeding in the next year. After eliciting this probability, the SAD posed scenarios for which the probability of being pulled over for speeding varied, first by randomly chosen values of 0.10, 0.20, or 0.30, and second for three times these values. For

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<sup>16</sup> See Ceccarini (2008) for an application of this idea.

each scenario, the SAD asked for the probability that the person would speed. For each scenario we calculate the following expected premium increase:

$$\begin{aligned}
 E[\Delta Premium \mid Speeding \ 15mph+] = & \\
 & E[\Delta Premium \mid Speeding \ 15mph + conviction] * \\
 & Prob(Speeding conviction \mid Pulled over for speeding \ 15mph+) * \\
 & Prob(Pulled over for speeding \mid Speeding \ 15mph+) \quad (7)
 \end{aligned}$$

We use individuals' subjective probabilities as elicited by the SAD for each of the four terms in eq. (7) at baseline and at the one-year follow-up, which yields six observations for each person.<sup>17</sup>

We pool these observations and estimate the following equation with individual respondent fixed effects and standard errors clustered at the individual level:

$$Subj. Prob. Speeding_t = \beta_0 + \beta_1 E_t[\Delta Premium \mid Speeding] + \varepsilon_t \quad t \in \{-1, 0\} \quad (8)$$

The coefficient of interest is  $\beta_1$ , which measures the mean individual change in subjective probability of speeding due to a given percent increase in premium. The null hypothesis is  $\beta_1 = 0$ —i.e., no moral hazard.

In addition, the SAD elicited the individual's subjective belief about the expected premium increase following a DWI conviction and the probability of drinking and driving in the next year given the person's subjective beliefs about a DWI conviction. Respondents were also asked the probability of drinking and driving if the expected premium increase doubled. We thus

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<sup>17</sup>The SAD asked for the subjective probability of being convicted for speeding conditional on speeding. In both waves the mean subjective probability of being pulled over for speeding, conditional on speeding, was 0.24 and the mean subjective probability of being convicted, also conditional on speeding, was about 0.5. This puzzling result may reflect the possibility that, at least in some of the SAD study cities, e.g., Seattle, the individual receives a speeding citation other than by being pulled over, such as by automated camera. Alternatively, some respondents may have interpreted the question about conviction as conditional on being stopped. Our calculation assumes the latter.

obtain four observations/person and follow the same approach as for the speeding scenarios to estimate eq. (7) with *Drinking and Driving* replacing *Speeding*.

### **C. Step 2. Relationship between Reckless Driving and Subjective Probability of an Accident**

The second step measures specific dimensions of private information that determine the residual component of individuals' subjective probabilities of an accident—the component not explained by the objective probability of an accident. The results of this analysis are reported above in Table 2.

### **D. Step 3. Relationship between Subjective Probability of an Accident and Ex Post Risk**

Third, we measure the relationship between the subjective probability of an accident and the ex post probability of an accident. The parameter estimate  $\beta_1$  from eq. (4) measures this relationship.

### **E. Results**

On average, the mean subjective probability of speeding 15+ mph over the speed limit in the next year is 0.45 at baseline and 0.40 at the follow-up interview (Table 6). In both waves the mean subjective probability of being pulled over for speeding 15+ mph, conditional on such speeding, is 0.24, and the mean subjective probability of being convicted, conditional on being pulled over for speeding, is about 0.5. The mean expected premium increase due to a speeding conviction is 0.28 at baseline and 0.33 at follow-up. In both waves the mean subjective probability of drinking and driving is 0.17, and the expected premium increase due to a DWI increased from 0.77 at baseline and 0.86 at follow-up. The mean subjective probability of being pulled over conditional on drinking and driving is 0.10 and 0.11 in the two waves, respectively. The probabilities of a DWI conviction conditional on being pulled over for drinking and driving are 0.60 and 0.61.

Doubling the expected premium increase from speeding leads to a 0.23 lower probability of speeding, and doubling the expected premium increase from drinking and driving leads to a 0.10 lower probability of drinking and driving (Table 7). These relationships capture the first step in Fig. 1. The parameter estimates on the subjective probability of speeding of 0.026 and 0.031 for the subjective probability of drinking and driving in the next year (Table 2, col. 2) capture the second step in Fig. 1. To measure the third step in Fig. 1, we use the parameter estimate on the subjective probability of an accident of 0.048 (Table 4, col. 2), and in sensitivity analysis, the parameter estimate on the subjective probability of 0.130 col. 4).

Table 8 summarizes the parameter estimates for each step in Fig. 1, for each of the two types of reckless driving. The product of the estimates from the three analysis steps for speeding is -0.0003 or -0.03 percent. Similarly, the corresponding effect for drinking and driving is -0.03 percent. Using the alternative estimate for the relationship between objective and subjective probability of an accident yields slightly higher estimates of -0.08 percent for speeding and -0.04 percent for drinking and driving. What makes the moral hazard effects so low is that the marginal effects of reckless driving on the probabilities of accidents are low. This is plausible for anyone who has observed the many speeders on a highway. Very few accidents result per speeding episode. In sum, the presence of asymmetric information in the automobile insurance market contributes substantially more to adverse selection than to moral hazard.

## **VI. Sorting of Policyholders Based on their Accident Risk**

### **A. Rationale for Sorting**

A major attribute of insurance markets is that insurers often reject applicants rather than sell insurance to all comers at an actuarially fair price plus a load for administrative and market expense plus profit. A commonly stated reason noted by insurers is that they cannot develop an

actuarially fair premium for some consumers. Hendren (2013) formalized this argument. In his framework, there are low- and high-risk types. For the low-risk types, consumers are likely to have little private information. However, high-risk individuals may consist of persons who were simply unlucky in the past in being involved in accidents and who filed claims for this reason and those who have private information about their risk type. The unlucky persons may have the ex ante accident risk of low-risk insureds. Hendren showed empirically that indeed high-risk persons who are rejected by insurers often possess additional private information about their risk types.

Hendren's empirical analysis encompassed markets for long-term care, disability, and life insurance, all types of coverage voluntarily demanded by consumers. By contrast, automobile liability insurance coverage is mandatory in nearly every state. So outright rejections are not a possibility, although insurers may reject applicants for coverage above the mandatory liability limits. Rejections of applications for automobile insurance are rare. According to the SAD, only 2.2 percent had been rejected by an insurer in the last three years at baseline and only 1.7 percent had been rejected in the past year at follow-up.

A plausible mechanism for harder-to-rate drivers in the automobile insurance market is for insurers to sort drivers on the basis of objective accident risk, as in Hendren (2013), with the difference being that the drivers are accepted for some level of coverage rather than being rejected outright, but the high-risk drivers "pay" for their additional risk in part by being insured by lower-quality insurers, where quality is measured by such attributes as poorer customer service, e.g., greater hassles in collecting from insurers, a smaller network of firms available for repairs of damage, and generally offering lower value for the money. By specializing, lower-quality insurers become specialized in gauging not-easily observed characteristics of their

customers and dealing with their “hard-luck” stories. Few respondents to the SAD were covered by surplus line insurers on high-risk pools.

Our empirical analysis of sorting in the automobile insurance market involves two steps. In Step 1, we show that higher-risk drivers measured on objective characteristics used by insurers for risk classification tended to be insured by lower-quality insurers. In Step 2, we show that higher-risk drivers based on the same objective characteristics tended to have more private information about their accident risk.

### **B. Step 1: Choice of Other Dimensions of Insurance Contracts**

We obtain data on insurers from three additional sources: J.D. Power, Insure.com, and *Consumer Reports*. Each of these sources report consumer ratings along multiple dimensions of quality for large automobile insurance companies. Insure.com also reports coverage options and discounts offered by each insurer that is included in the study. The large insurers reported in these studies cover approximately 83 percent of our sample for J.D. Power ratings and 77 percent of our data for *Consumer Reports* ratings and Insure.com ratings and insurer characteristics.

*Consumer Reports*, available online by subscription, publishes automobile insurance ratings based on a survey of 102,207 subscribers. The *reader score* is a measure of overall satisfaction with claims handling based on the subsample of 29,116 survey respondents who had a claim during 2009 to mid-2012. The score ranges from 0 to 100, where 100 indicates all respondents are completely satisfied; 80, very satisfied; 60, fairly well satisfied; and 40, somewhat dissatisfied on average. The *premium satisfaction* rating reflects satisfaction with premium paid based on the entire sample, and it varies from 1 to 5, increasing in satisfaction.

Insure.com published ratings of 20 large automobile insurance companies based on a survey of 5,600 insurance customers conducted from September-November 2012. The *overall*



*score*, which varies from 0 to 100, is an aggregate measure of: satisfaction with claims processing, customer service; premium paid given the coverage; the percent of respondents who said they would renew their coverage (*plan to renew*); and the percent of respondents who said they would recommend or already recommended the insurer. Insure.com also reports coverage options, including whether or not the company offers accident forgiveness (*accident forgiveness offered*), and a distribution of reasons that respondents bought from the company (e.g., *saw commercial*).

J.D. Power also publishes customer satisfaction ratings of U.S. automobile insurance companies online. It also reports ratings of customers' claims experience, as does *Consumer Reports*, they also report ratings based on customers' experience purchasing a new automobile insurance policy. Ratings include: (1) *overall claims satisfaction*, (2) *overall purchase experience*, (3) *claims service interaction*, which is based on claimants' ratings of the insurer representative or agent handling the claim, and (4) *local agent interaction*, which reflects purchasers' experiences interacting with the insurer's local agent or staff. All ratings vary from 2 to 5, where 5 is among the best, 4 better than most, 3 average, and 2 the rest.

Given that private information affects individuals' choice of the level of liability coverage to purchase, a question remains whether private information affects individuals' choice of insurer based on other dimensions of insurance contracts such as coverage options, discounts, and insurer quality scores. We base empirical tests of the effect of private information on choices concerning other coverage attributes using the following general specification.

$$Attribute_{t-1} = \beta_0 + \beta_1 Subj.Prob.Accident_{t-1} + \beta_2 X_{t-1} + \varepsilon_{t-1} \quad (9),$$

where *Attribute* alternatively measures consumers' ratings, policy options, or discounts reported in *Consumer Reports*, Insure.com, or J.D. Power for the SAD respondent's insurer. Of particular

interest are the parameter estimates on the vector  $\beta_1$  from each equation. If  $\beta_1 \neq 0$  in eq. (9), then an individual's subjective probability is related to the attribute represented by the dependent variable.

Table 9 reports the results of estimating these two sets of equations on the subsample of SAD respondents whose insurers have a reported value for a particular attribute. Panel A includes attributes measuring the overall quality of an insurance contract. An individual with a higher objective probability of an accident is more likely to be insured by a low quality insurer (Panel A, cols. 2, 4, 6, 8, and 10). This result is consistent with sorting based on observable risk and is robust across many different measures of overall quality. Relative to their objective counterparts, the estimated parameters on the subjective probability of an accident are generally small, albeit positive, and mostly statistically insignificant. Conditional on the objective accident probability, individuals with a higher subjective belief of an accident are more likely to choose a high quality insurer. An individual with private information about his risk type is likely to put more effort into seeking a high quality insurer relative to an individual with the same observable risk type but no private information because he anticipates that his true risk type will be revealed over time and he would prefer to be with an insurer with a high rating, which reflects claims and premium satisfaction.

Panel B includes specific quality attributes of an insurance contract. Individuals with high objective accident risk tend to have insurers with lower premium satisfaction, claims service interaction, and local agent interaction scores. They are more likely to have a policy with accident forgiveness and more likely to be insured by an insurer with a high proportion of customers who bought from that insurer because they saw a commercial. With the exception of premium satisfaction, coefficients on the covariate for the subjective probability of an accident

are insignificant and vary in sign. For premium satisfaction, the coefficients are positive and significant at the 0.10 level or better. A plausible reason is that high-risk individuals think that they have a higher probability of an accident than the insurer does and the insurer's prediction determines the premium.

These findings suggest a number of mechanisms by which sorting occurs in the market for automobile insurance. First, dissatisfaction with premiums based on the objective probability of an accident simply reflects consumer dissatisfaction with paying experience-rated premiums. Second, dissatisfaction with claims service and local agents could also reflect provision of lower quality service by insurers frequented by drivers with a high objective accident risk. Moreover, since lower-quality drivers have more accidents, they have more negative interactions with their insurers. Accident-free drivers have less reason to complain about poor service. Third, people with high accident probabilities would understandably be more likely to rely on commercials for information about insurers than rely on advice from friends who might be reluctant to encourage an accident-prone friend to purchase coverage from their insurers.

### **C. Step 2: Private Information by Risk Type**

To gauge the importance of private information for persons with difference objective accident risk, we rank order the sample by predicted accident risk and split the sample into terciles according to the objective accident probability. We re-estimate eq. (3) with the sample split into terciles, low, medium, and high objective accident risk. The dependent variable is a binary for whether or not the respondent had an accident during the follow-up year. The explanatory variables are the subjective probability of an accident during the follow-up year and the objective risk of an accident during this period.

The results are striking (Table 10). The high-risk tercile has private information about accident risk that could not be detected across the whole sample or for the low and medium (objective) risk individuals. This leads to the conclusion that as insurers suspect, drivers who are classified as high risk have private information about their accident risk that drivers in the other risk categories do not possess.

## **VII. Discussion and Conclusion**

Not surprisingly, the information insurers routinely collect on their customers predicts the objective probability of an accident during the policy year. Factors such as youth, gender, miles driven/year, and prior speeding citations and arrests for DWI, are predictive of the probability of an accident. The subjective probability of an accident in the following year is systematically related to the individual's projection of his or own care in driving. It is not only possible to elicit subjective probabilities of speeding 15 or more miles per hour over the speed limit and of drinking and driving during the past year, but these probabilities are systematically related to subjective beliefs about having an accident. People make judgments about the quality of their own driving ability that are systematically related to their subjective probabilities of having an accident. And the objective probability of an accident is positively related to its subjective counterpart.

We find that drivers who reported higher subjective probabilities of an accident in the following year were more likely to purchase more complete liability insurance coverage after accounting for the probability of an accident based on information used by insurers in risk classification.

Findings from positive correlation tests and bivariate probit analysis also show a positive relationship between maximum exposure to loss from an automobile accident and ex post

accident risk. However, this relationship is consistent with both adverse selection and moral hazard. Using a series of questions posed by our survey, we estimate the amount of moral hazard to be very small, which implies that the positive correlation test and bivariate probit results mainly reflect adverse selection, which is consistent with our earlier results showing that persons with higher subjective beliefs about the probability of an accident in the following year tend to purchase more complete liability coverage. Along the way to determining the extent of moral hazard, we document that persons who expected higher premium increases conditional on their being cited for speeding 15 miles per hour and over and arrested for drinking and driving have lower subjective probabilities of speeding and drinking and driving, suggesting a deterrent effect from imposing higher premium penalties on reckless driving.

Unlike most other lines of insurance, state laws require that drivers purchase a minimum level of liability insurance coverage. Thus, even in the presence of asymmetric information, there will be no unraveling of coverage at the statutorily-determined levels of liability coverage. There could be unraveling of contracts offering deeper coverage and collision coverage, but we do not observe this. Most respondents to our survey had liability coverage well above the statutory liability limits. One mechanism that mitigates unraveling of the latter contract types is sorting of insured by objective risk. Sorting may reduce the adverse effects of private information by, for example, making it more difficult for accident-prone drivers to collect damages since they are more likely to have a lower-quality insurer. Persons classified as high risk on objective factors which insurers use in risk classification do possess more private information about their accident risk, but insurers that specialize in covering such individuals can account for this in premium-setting given segmentation in this market. Our findings on sorting are new.

Another factor making unraveling less likely in the automobile insurance market is that

claims frequency is relatively high and the claims tail is relatively short compared to other lines of third-party insurance, such as medical malpractice insurance. Thus, to the extent that there is learning about customer riskiness, it occurs fairly rapidly.

When we began this study, we sought an answer to the question of why in the presence of adverse selection insurers do not obtain more information about their customers. The answer seems to be that they do not have to. Drivers with a high accident risk, as determined by objective factors used in risk classification, are more likely to possess private (Frank A Sloan and Chepke 2008) information about their driving skills and risk-taking propensities. According to our survey, insurers outright rejected very few persons outright. Rather than formally reject applicants, there are more subtle mechanisms for rejecting high-risk drivers, an example being a receptionist in a high-quality insurer's office advising a high-risk driver to take his business elsewhere. Poorer drivers pay more, not only in terms of higher premiums but in lower-quality service.

According to the old adage, "If it ain't broke, don't fix it." In the automobile insurance market, institutional responses by private firms have done the fixing. Although there are minor suggestions, e.g., highly experience-rated premiums may deter reckless driving, in contrast to other lines of insurance, such as medical malpractice insurance and workers' compensation, there is no important constituency for reform. Rather, empirical research on risk perceptions as in this study clarifies the role and sources of private information and market responses for coping with it.

### Acknowledgements

This paper was funded in part by a grant from the National Institute on Alcohol Abuse and Alcoholism (NIAAA, #R01AA017913-01A1). The sponsor had no role in the design or conduct of this study. There are no conflicts of interest nor any financial disclosures for any of the authors. We also thank Hanming Fang, University of Pennsylvania, and Ahmed Khwaja, Yale University, for their collaboration in writing the proposal that led to the grant, and for assistance in developing the questionnaire used in this study.

## REFERENCES

- Abbring, J. H., Heckman, J. J., Chiappori, P. A., & Piquet, J. (2003). Adverse selection and moral hazard in insurance: Can dynamic data help to distinguish? *Journal of the European Economic Association*, 1(2 - 3), 512-521.
- Barseghyan, L., Prince, J., & Teitelbaum, J. C. (2011). Are risk preferences stable across contexts? Evidence from insurance data. *The American Economic Review*, 101(2), 591-631.
- Barsky, R. B., Juster, F. T., Kimball, M. S., & Shapiro, M. D. (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *The Quarterly Journal of Economics*, 112(2), 537-579.
- Ceccarini, O. (2008). *Does experience rating matter in reducing accident probabilities? A test for moral hazard*. University of Pennsylvania, Philadelphia, PA.
- Chiappori, P. A., & Salanie, B. (2000). Testing for asymmetric information in insurance markets. *Journal of Political Economy*, 108(1), 56-78.
- Cutler, D., & Reber, S. (1998). Paying for health insurance: The trade-off between competition and adverse selection. *Quarterly Journal of Economics*, 113(2), 433-466.
- Einav, L., Finkelstein, A., Pascu, I., & Cullen, M. (2012). How general are risk preferences? Choices under uncertainty in different domains. *American Economic Review*, 102(6), 2606-2638.
- Fang, H., Keane, Michael P., & Silverman, D. (2008). Sources of advantageous selection: Evidence from the medigap insurance market. *Journal of Political Economy*, 116(2), 303-350, doi:10.1086/587623.
- Finkelstein, A., & McGarry, K. (2006). Multiple dimensions of private information: Evidence from the long-term care insurance market. *American Economic Review*, 96(4), 938-958, doi:doi: 10.1257/aer.96.4.938.
- Finkelstein, A., & Poterba, J. (2004). Adverse selections in insurance markets: Policyholder evidence from the U.K. annuity market. *Journal of Political Economy*, 112(1), 183-208.
- Gruber, J., & Köszegi, B. (2001). Is addiction "rational"? Theory and evidence. *The Quarterly Journal of Economics*, 116(4), 1261-1303.
- Guck, T. P., Elsasser, G. N., Kavan, M. G., & Eugene, J. (2003). Depression and congestive heart failure. *Congestive Heart Failure*, 9(3), 163-169.
- Hendren, N. (2013). Private information and insurance rejections. *Econometrica*, 81(5), 1713-1762, doi:10.3982/ecta10931.
- Hepburn, S. R., Barnhofer, T., & Williams, J. M. G. (2009). The future is bright? Effects of mood on perception of the future. *Journal of Happiness Studies*, 10(4), 483-496.
- Khwaja, A., Sloan, F., & Wang, Y. (2009). Do smokers value their health and longevity less? *Journal of Law and Economics*, 52(1), 171-196.
- Lemaire, J. (1995). *Bonus-malus systems in automobile insurance (Vol. 19)*: Springer.
- Lieberman, J. A. (2003). The differential diagnosis of fatigue and excessive dysfunction in primary care. *Journal of Clinical Psychiatry*, 64(Suppl. 14), 40-43.



- Loewenstein, G., Weber, R., Flory, J., Manuck, S., & Muldoon, M. (2001). Dimensions of time discounting. Paper presented at the Conference on Survey Research on Household Expectations and Preferences, Ann Arbor, MI,
- Madden, G. J., & Johnson, P. S. (2010). A discounting primer. In G. J. Madden, & W. K. Bickel (Eds.), *Impulsivity: The behavioral and neurological science of discounting* (pp. 11-37). Washington, D.C.: American Psychological Association.
- National Institute on Alcohol Abuse and Alcoholism (2009). Per capita ethanol consumption for states, census regions, and the United States, 1970–2007 (Gallons of ethanol, based on population age 14 and older)
- Office of the Commissioner of Insurance (2011). *Consumer's guide to auto insurance*. Madison, WI: Office of the Commissioner of Insurance.
- Pennsylvania Insurance Department (2013). *Questions and answers: A supplement to the Automobile Insurance Guide*.  
[http://www.portal.state.pa.us/portal/server.pt/community/auto\\_insurance/9187/auto\\_insurance\\_questions\\_and\\_answers/590976](http://www.portal.state.pa.us/portal/server.pt/community/auto_insurance/9187/auto_insurance_questions_and_answers/590976). Accessed February 12 2014.
- Perreira, K. M., & Sloan, F. A. (2002). Excess alcohol consumption and health outcomes: a 6 - year follow - up of men over age 50 from the health and retirement study. *Addiction*, 97(3), 301-310.
- Rothchild, M., & Stiglitz, J. (1976). Equilibrium in competitive insurance markets: An essay on the economics of imperfect information. *The Quarterly Journal of Economics*, 90(4), 629-629.
- Shavell, S. (2005). Minimum asset requirements and compulsory liability insurance as solutions to the judgment-proof problem. *RAND Journal of Economics*, 36(1), 63-77.
- Sloan, F. A., & Chepke, L. M. (2008). *Medical malpractice*. Cambridge, MA: MIT Press.
- Sloan, F. A., & Eldred, L. M. (2013). Do preferences of drinker-drivers differ? [Working paper].
- Sloan, F. A., Eldred, L. M., Guo, T., & Xu, Y. (2013). Are people overoptimistic about the effects of heavy drinking. *Journal of Risk and Uncertainty*, 47(1), 93-127.
- Sloan, F. A., Viscusi, W. K., Chesson, H. W., Conover, C. J., & Whetten-Goldstein, K. (1998). Alternative approaches to valuing intangible health losses: The evidence for multiple sclerosis. *Journal of Health Economics*, 17(4), 475-497, doi:10.1016/s0167-6296(97)00025-8.
- Smith, E., & Wright, R. (1992). Why is automobile insurance in Philadelphia so damn expensive? *The American Economic Review*, 82(4), 756-772.
- Ulleberg, P., & Rundmo, T. (2003). Personality, attitudes and risk perception as predictors of risky driving behaviour among young drivers. *Safety Science*, 41(5), 427-443.
- Wise, M., G., & Rundell, J. R. (1994). *Concise guide to consultation psychiatry*. Washington, D.C.: American Psychiatry Press.

Table 1 — Objective probability of an accident based on characteristics used by the insurer

	Mean (1)		Any accident (2)		Any chargeable accident (3)		Any non-chargeable accident (4)	
<i>Mean of dependent variable:</i>			0.213		0.035		0.187	
<i>Demographic characteristics</i>								
Male <25	0.021	(0.144)	0.196 **	(0.084)	0.022	(0.038)	0.194 **	(0.080)
Female <25	0.041	(0.198)	0.112 *	(0.062)	0.053 *	(0.028)	0.045	(0.059)
Married	0.466	(0.497)	-0.060 **	(0.025)	-0.015	(0.011)	-0.053 **	(0.024)
<i>Driving characteristics</i>								
Miles > 15k/yr	0.154	(0.360)	0.116 ***	(0.034)	0.061 ***	(0.015)	0.064 **	(0.032)
Drives to work	0.760	(0.429)	0.015	(0.029)	-0.001	(0.013)	0.006	(0.028)
Drives for work	0.321	(0.467)	0.033	(0.026)	-0.019	(0.012)	0.053 **	(0.025)
Speeding violations	0.526	(1.280)	0.033 ***	(0.009)	0.006	(0.004)	0.032 ***	(0.009)
DWI arrests	0.039	(0.299)	0.083 *	(0.043)	0.026	(0.019)	0.051	(0.041)
<i>Vehicle characteristics</i>								
Age	8.548	(5.592)	-0.002	(0.002)	0.001	(0.001)	-0.003	(0.002)
<i>Type</i>								
Sedan (omitted)	0.613	(0.487)						
Sport	0.026	(0.158)	-0.130 *	(0.076)	-0.003	(0.034)	-0.137 *	(0.072)
SUV	0.219	(0.415)	0.025	(0.030)	-0.011	(0.013)	0.043	(0.028)
Minivan	0.060	(0.237)	-0.026	(0.051)	-0.012	(0.023)	-0.021	(0.049)
Truck	0.070	(0.255)	0.045	(0.048)	0.015	(0.022)	0.023	(0.046)
Unknown	0.014	(0.116)	-0.066	(0.245)	0.025	(0.111)	-0.103	(0.234)
<i>City</i>								
Raleigh (omitted)	0.386	(0.487)						
Hickory	0.059	(0.235)	0.003	(0.053)	0.055 **	(0.024)	-0.050	(0.050)
Seattle	0.164	(0.371)	0.028	(0.035)	-0.016	(0.016)	0.040	(0.034)
Yakima	0.039	(0.194)	-0.123 *	(0.063)	0.008	(0.028)	-0.141 **	(0.060)
Milwaukee	0.110	(0.313)	-0.064	(0.040)	-0.036 **	(0.018)	-0.041	(0.038)
Lacrosse	0.081	(0.272)	-0.072	(0.046)	-0.020	(0.021)	-0.062	(0.044)
Philadelphia	0.115	(0.319)	-0.012	(0.040)	-0.012	(0.018)	-0.008	(0.038)
Wilkes-Barre	0.048	(0.213)	-0.057	(0.057)	-0.024	(0.026)	-0.046	(0.055)
<i>Constant</i>			0.207 ***	(0.039)	0.035 **	(0.018)	0.190 ***	(0.038)
<i>N</i>	1,177							
<i>R<sup>2</sup></i>			0.063		0.044		0.056	

Standard errors in parentheses

\* p&lt;0.10 \*\* p&lt;0.05 \*\*\* p&lt;0.01

Dependent variable is binary indicator for accidents reported in Wave 1

Table 2 — Relationship between subjective probability of an accident and other information

	Mean		Subjective probability of accident	
	(1)		(2)	
<i>Dependent variable:</i>	0.135	(0.146)		
<i>Private information</i>	0.000	(0.000)		
<i>Driving self-rating</i>	0.000	(0.000)		
Worse than others	0.023	(0.150)	0.099 ***	(0.030)
About the same as others	0.247	(0.432)	0.041 ***	(0.012)
Better than others	0.492	(0.499)	0.029 ***	(0.011)
Much better than others (omitted)	0.238	(0.013)		
<i>Financial risk tolerance</i>				
Least financially risk tolerant	0.357	(0.479)	0.012	(0.022)
Moderately financially risk tolerant	0.599	(0.489)	0.006	(0.021)
Most financially risk tolerant (omitted)	0.044	(0.006)		
<i>Driving risk tolerance</i>				
Do not speed (least risk tolerant)	0.253	(0.435)	0.002	(0.013)
Speed <10 mph (moderately risk tolerant)	0.512	(0.499)	-0.011	(0.011)
Speed 15 mph (most risk tolerant) (omitted)	0.235	(0.013)		
Cognitive ability (0-16)	14.470	(1.741)	-0.003	(0.003)
Impulsivity (increasing)	37.090	(3.476)	-0.002 **	(0.001)
Depressed (binary)	0.182	(0.385)	-0.011	(0.011)
Altruism (non-familial)	23.000	(2.619)	0.002	(0.002)
WTP to avoid paralysis (monthly)	36.790	(33.952)	0.000	(0.000)
Subjective prob. of speeding	0.449	(0.398)	0.026 **	(0.012)
Subjective prob. of drinking and driving	0.165	(0.292)	0.031 **	(0.015)
<i>Demographic information</i>				
Household income (\$100k)	0.811	(0.641)	-0.021 ***	(0.007)
Education (years)	15.610	(1.944)	0.000	(0.002)
Non-white	0.130	(0.337)	-0.010	(0.013)
<i>Objective probability of accident</i>	0.214	(0.103)	0.179 ***	(0.043)
<i>Constant</i>			0.169 **	(0.080)
<i>N</i>	1,139			
<i>R</i> <sup>2</sup>			0.073	

Standard errors in parentheses

\* p<0.10 \*\* p<0.05 \*\*\* p<0.01

Table 3 — Relationship between insurance coverage and subjective and objective probability of an accident

	Mean (std. dev.)				OLS			
	Liability		Collision		Liability		Collision	
	Liability exposure (\$100k) (1)	Liability exposure   Has liability insurance (2)	No collision insurance   Has liability insurance (3)	Deductible > \$500   Has collision insurance (4)	Liability exposure (\$100k) (5)	Liability exposure   Has liability insurance (6)	No collision insurance   Has liability insurance (7)	Deductible > \$500   Has collision insurance (8)
<i>Dependent variables:</i>								
Liability exposure (\$100k)	1.967 (5.45)	2.007 (5.536)						
No collision insurance   Has liability insurance			0.138 (0.346)					
Deductible > \$500   Has collision insurance				0.163 (0.370)				
<i>Independent variables:</i>								
Subjective probability of accident	0.134 (0.141)	0.133 (0.140)	0.134 (0.144)	0.152 (0.703)	-4.207 *** (1.255)	-4.574 *** (1.329)	-0.086 (0.073)	0.071 (0.085)
Objective probability of accident	0.210 (0.099)	0.210 (0.098)	0.213 (0.102)	0.210 (0.098)	2.130 (1.789)	2.064 (1.884)	0.178 * (0.103)	0.183 (0.124)
Constant					2.057 *** (0.375)	2.148 *** (0.392)	0.112 *** (0.025)	0.111 *** (0.03)
<i>N</i>	970	915	1,108	934	970	915	1,108	934
<i>R</i> <sup>2</sup>					0.012	0.013	0.004	0.009

Standard errors in parentheses

Exposure regressions exclude individuals with indeterminate liability limits (1,000 <= Upper Limit < State Minimum).

\* p<0.10 \*\* p<0.05 \*\*\* p<0.01

Table 4 — Relationship between accident occurrence and subjective probability of an accident

	Any accident		Number of accidents		Number of chargeable accidents		Number of non-chargeable accidents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Subjective probability of accident	0.077 (0.058)	0.048 (0.058)	0.170 ** (0.067)	0.130 * (0.067)	0.081 *** (0.024)	0.076 *** (0.024)	0.084 (0.061)	0.050 (0.061)
Objective probability of accident		0.300 *** (0.081)		0.410 *** (0.094)		0.054 (0.034)		0.360 *** (0.085)
Constant	0.079 *** (0.011)	0.019 (0.02)	0.076 *** (0.013)	-0.006 (0.023)	0.002 (0.005)	-0.009 (0.008)	0.074 *** (0.012)	0.002 (0.021)
Observations	1,173	1,172	1,173	1,172	1,173	1,172	1,173	1,172
R <sup>2</sup>	0.002	0.013	0.006	0.021	0.010	0.012	0.002	0.017

Standard errors in parentheses

\* p<0.10 \*\* p<0.05 \*\*\* p<0.01

Subjective probability of accident is measured in the baseline year.

Accident occurrence is measured in the follow-up year.

Table 5 — Relationship between accident occurrence and insurance coverage

	Mean (1)	Any accident (2)	Any accident (3)
<i>Panel A: Linear Probability Model</i>			
<i>Dependent variable:</i>	0.089	(0.009)	
<i>Liability insurance</i>			
Fully insured (zero exposure)	0.455	(0.015)	0.047 ** (0.022) 0.044 ** (0.022)
Exposure level if <= \$225k	0.579	(0.037)	0.011 (0.022) 0.011 (0.022)
Exposure level if > \$225k	8.575	(0.619)	0.001 (0.002) 0.000 (0.002)
<i>Collision insurance</i>			
Deductible > \$500	0.122	(0.010)	0.018 (0.032) 0.019 (0.032)
Deductible <=\$500	0.680	(0.014)	-0.012 (0.023) -0.009 (0.023)
Objective probability of accident	0.210	(0.003)	0.340 ***
Constant			0.069 *** (0.025) -0.003 (0.031)
<i>N</i>	1,082		1,083 1,082
<i>R</i> <sup>2</sup>			0.006 0.020
<i>Panel B: Bivariate probit</i>			
	Whole sample (1)	Has liability insurance (2)	
<i>Correlation coefficient</i>	0.150 ** (0.073)	0.137 * (0.075)	
<i>Coefficients in Accident equation</i>			
Objective probability of accident	1.930 *** (0.546)	2.162 *** (0.561)	
Constant	-1.773 *** (0.138)	-1.809 *** (0.142)	
<i>Coefficients in Zero exposure equation</i>			
Objective probability of accident	0.424 (0.409)	0.540 (0.428)	
Constant	-0.071 (0.095)	-0.048 (0.099)	
<i>N</i>	970	911	

Standard errors in parentheses

Exposure regressions exclude individuals with indeterminate liability limits.

\* p<0.10 \*\* p<0.05 \*\*\* p<0.01

Table 6 — Subjective probabilities and expected premium increases due to reckless driving

	Mean	Std. dev.
<i>Speeding</i>		
Subjective prob. of speeding 15mph+	0.45	0.40
Subjective prob. of speeding 15mph+ (2)	0.40	0.39
Subjective prob. of being pulled over   Speeding 15mph+	0.24	0.25
Subjective prob. of being pulled over   Speeding 15mph+ (2)	0.24	0.23
Subjective prob. of speeding conviction   Speeding 15mph+	0.51	0.37
Subjective prob. of speeding conviction   Speeding 15mph+ (2)	0.50	0.36
Expected premium increase   Speeding 15mph+ conviction	0.28	0.28
Expected premium increase   Speeding 15mph+ conviction (2)	0.33	0.35
<i>Drinking and driving</i>		
Subjective prob. of drinking and driving	0.17	0.30
Subjective prob. of drinking and driving (2)	0.17	0.30
Subjective prob. of being pulled over   Drinking and driving*	0.10	0.13
Subjective prob. of being pulled over   Drinking and driving* (2)	0.11	0.13
Subjective prob. of DWI conviction   Pulled over for drinking and driving*	0.60	0.33
Subjective prob. of DWI conviction   Pulled over for drinking and driving* (2)	0.61	0.32
Expected premium increase   DWI conviction	0.77	1.17
Expected premium increase   DWI conviction (2)	0.86	0.93
<i>Observations</i>	1,119	

Excludes individuals without liability insurance

(2) indicates a question elicited in Wave 3; otherwise, Wave 2

\* This question relates specifically to weekend drinking and driving.

Table 7 — Relationship between subjective probability of reckless driving and premium increase

	Mean (1)	Subjective prob. of speeding 15mph+ (2)	Subjective prob. of drinking and driving (3)
<i>Dependent variables</i>			
Subjective prob. of speeding 15mph+	0.390 (0.392)		
Subjective prob. of drinking and driving	0.120 (0.261)		
<i>Independent variables</i>			
Expected premium increase   Speeding 15mph+	0.053 (0.124)	-0.230 *** (0.071)	
Expected premium increase   Drinking and driving	0.076 (0.170)		-0.097 *** (0.021)
<i>Constant</i>		0.390 *** (0.005)	0.120 *** (0.002)
<i>Observations</i>	4,270	6,350	4,421
<i>R<sup>2</sup></i>		0.007	0.011

Standard errors in parentheses

\* p<0.10 \*\* p<0.05 \*\*\* p<0.01

Excludes individuals without liability insurance

Expected premium increase | Speeding 15mph+ =

E[Premium increase|Speeding conviction] \*

P(Speeding conviction|Pulled over) \*

P(Pulled over|Speeding 15mph+)

Expected premium increase | Drinking and driving =

E[Premium increase|DWI conviction] \*

P(DWI conviction|Pulled over) \*

P(Pulled over|Weekend drinking and driving)



Table 8 — Moral Hazard

	Speeding	Drinking and driving
<b>Main Analysis</b>		
$\Delta$ Subj. prob. of reckless driving / $\Delta$ Penalty	-0.230 ***	-0.097 ***
$\Delta$ Subj. prob. of accident / $\Delta$ Subj. prob. of reckless driving	0.026 **	0.031 **
$\Delta$ Obj. prob. of accident / $\Delta$ Subj. prob. of accident	0.048	0.048
$\Delta$ Obj. prob. of accident / $\Delta$ Penalty	-0.0003	-0.0001
<b>Sensitivity analysis</b>		
$\Delta$ Subj. prob. of reckless driving / $\Delta$ Penalty	-0.230 ***	-0.097 ***
$\Delta$ Subj. prob. of accident / $\Delta$ Subj. prob. of reckless driving	0.026 **	0.031 **
$\Delta$ Obj. prob. of accident / $\Delta$ Subj. prob. of accident	0.130 *	0.130 *
$\Delta$ Obj. prob. of accident / $\Delta$ Penalty	-0.0008	-0.0004

$\Delta$  Penalty = 100% increase in premium

Excludes individuals without liability insurance

\* p<0.10 \*\* p<0.05 \*\*\* p<0.01

Table 9 — Private information and quality of insurer

	Reader score <i>Consumer Reports</i>		Overall score <i>Insure.com</i>		Overall claims satisfaction <i>J.D. Power</i>		Overall purchase experience <i>J.D. Power</i>		Plan to renew <i>Insure.com</i>	
<i>Panel A: Overall quality of insurer</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Subjective probability of accident	0.617 (0.462)	0.815 * (0.464)	0.574 (0.843)	0.769 (0.849)	0.110 (0.141)	0.148 (0.142)	0.162 (0.216)	0.241 (0.217)	-0.089 (1.254)	0.449 (1.256)
Objective probability of accident		-2.083 *** (0.668)		-2.197 * (1.225)		-0.397 * (0.204)		-0.836 ** (0.310)		-6.057 *** (1.813)
<i>N</i>	794	794	787	787	803	803	821	821	787	787
<i>R</i> <sup>2</sup>	0.026	0.038	0.010	0.015	0.009	0.014	0.029	0.038	0.019	0.032
<i>Demographics</i>	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

  

	Premium satisfaction <i>Consumer Reports</i>		Claims service interaction <i>J.D. Power</i>		Local agent interaction <i>J.D. Power</i>		Accident forgiveness offered <i>Insure.com</i>		Reason for buying: saw commercial <i>Insure.com</i>	
<i>Panel B: Specific quality attributes</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Subjective probability of accident	0.243 * (0.131)	0.298 ** (0.132)	-0.095 (0.277)	-0.022 (0.279)	-0.188 (0.262)	-0.124 (0.264)	0.153 (0.108)	0.117 (0.109)	-0.439 (0.859)	-0.701 (0.864)
Objective probability of accident		-0.576 *** (0.190)		-0.755 * (0.401)		-0.718 * (0.378)		0.382 ** (0.158)		2.949 ** (1.247)
<i>N</i>	794	794	803	803	795	795	822	822	787	787
<i>R</i> <sup>2</sup>	0.018	0.029	0.023	0.027	0.019	0.024	0.014	0.021	0.022	0.029
<i>Demographics</i>	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors in parentheses

Demographics included are income, education, and race

\* p<0.10 \*\* p<0.05 \*\*\* p<0.01

Table 10 — Private information about risk type by objective risk terciles

	Accident		
	Tercile 1	Tercile 2	Tercile 3
	(1)	(2)	(3)
Subjective probability of accident	-0.013 (0.081)	-0.186 * (0.109)	0.281 *** (0.105)
Objective probability of accident	-0.048 (0.256)	0.768 (0.745)	0.287 (0.195)
Constant	0.054 * (0.033)	-0.028 (0.149)	-0.017 (0.066)
Observations	383	385	383
R <sup>2</sup>	0.000	0.010	0.027

Standard errors in parentheses

\* p<0.10 \*\* p<0.05 \*\*\* p<0.01