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Advantageous Selection, Moral Hazard, and Insurer Sorting on Risk in the U.S. Automobile Insurance Market

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Abstract

This study quantifies the role of private information in automobile insurance policy choice using data on subjective beliefs, risk preference, reckless driving, the respondent's insurer and insurance policy characteristics merged with insurer-specific quality ratings distributed by independent organizations. We find a zero correlation between ex post accident risk and insurance coverage, reflecting advantageous selection in policy choice offset by moral hazard. Advantageous selection is partly attributable to insurer sorting on consumer attributes known and used by insurers. Our analysis of insurer sorting reveals that lower-risk drivers on attributes observed by insurers obtain coverage from insurers with higher-quality ratings.

Keywords

adverse selection; moral hazard; automobile insurance; private information; advantageous selection

I. Introduction

Empirical studies of insurance purchase decisions have demonstrated that consumers possess private information when purchasing, and their private information comes in multi-dimensional forms (e.g., Fang, Keane, and Silverman 2008). This information pertains to risk types (Rothchild and Stiglitz 1976), but also preferences, such as risk aversion, thrill seeking, tastes for goods leading to risk taking, e.g., alcohol, and in subjective beliefs about adverse consequences of risky behaviors. Individuals also differ in cognitive ability, which affects knowledge of the law and adverse consequences of risky behaviors, and, for driving, in their altruism toward other drivers, and in driving skills. While research has documented that multidimensional sources of private information exist, much remains to be learned about what these sources are, and how they vary by insurance type, and how they affect functioning of insurance markets.

Even though private information is a source of adverse selection in insurance markets and the notion that purchasers of insurance possess some private information is widely accepted, not all studies have found adverse selection (e.g., Cohen and Siegelman 2010). A frequently

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used method for determining whether there is adverse selection is the positive correlation test, where the correlation is between insurance quantity purchased and losses incurred during the policy year. Several studies of automobile insurance have reported a zero correlation between insurance coverage and accident risk (Chiappori and Salanie 2000; Dionne, Gauthier, and Vanasse 2001; Saito 2006).¹ A deficiency of this test is that a positive correlation can reflect both adverse selection and moral hazard. Disentangling the two is not straightforward (Bajari et al. 2014; de Meza and Webb 2001). Also, a zero correlation may reflect multidimensional private information (Finkelstein and McGarry 2006).

In the standard model of insurance choice, insurers are passive agents. Insurance markets persist in the presence of private information and with government requirements that certain types of information known to insurers not be explicitly used in premium setting or underwriting. Insurers must have learned how to cope with such private information. Yet research on this topic is still in its infancy (Baker and Swedloff 2013).

This study uses unique data from a survey of persons who both drove and consumed alcohol conducted for our research in four U.S. states—North Carolina, Pennsylvania, Washington, and Wisconsin. Our survey obtained information on various sources of private information, e.g., respondents' subjective probabilities about engaging in future behaviors and of experiencing adverse driving outcomes, risk preference, other preferences including altruism, income, wealth, motor vehicle ownership, and respondents' driving habits, and demographic characteristics. The survey asked for the respondent's automobile insurer and amounts of third-party and first-party insurance the person had, and the premium paid. Having the automobile insurer's name, we merge quality ratings obtained from several independent sources with the survey data. To our knowledge, no prior study has had as much information on insurance purchasers and choices as we do. A major strength of our survey is that it obtained objective measures of risk at the follow-up interview that are comparable to measures of subjective beliefs obtained at baseline about a year earlier, which allows for within-sample comparisons.

We find that there is advantageous selection in choice of automobile liability insurance coverage, and there is moral hazard. The advantageous selection reflects market responses on the supply side. In particular, risks are segmented based on factors predictive of the probability of an accident, both observed and used by insurers. The result is that lower-risk drivers are insured by higher quality insurers and conversely. Thus, even with various forms of government intervention, stratifying on risk eliminates much of the heterogeneity in accident risk among drivers and segregates higher-risk drivers in their own risk pools. Such sorting reduces cross subsidies from low- to high-risk drivers, and makes automobile insurance relatively attractive to low-risk purchasers, which is reflected in the advantageous selection we observe.

¹The above studies are based on North American data. In a German study, correlations were either zero or small and positive (Spindler, Winter, and Hagmayer 2014). Positive correlations were found in studies using French (Chiappori et al. 2006) and Israeli (Cohen 2005) data.

Our analysis proceeds in two stages. First, we assess consumers' private information about risk type and its role in insurance choices and accident risk. To study selection on observed dimensions of private information, we use standard techniques (e.g., Finkelstein and McGarry 2006). Following others (Chiappori and Salanie 2000; Finkelstein and Poterba 2004), we measure the correlation between insurance coverage choice and ex post accident risk. We then measure moral hazard directly.² Second, we investigate sorting of drivers among insurers based on predictors of drivers' accident risk as a response to potential selection and moral hazard in this market. Lower-risk drivers obtain coverage from insurers rated as having higher quality by independent agencies. Some insurers eschew the risky drivers on criteria observable to insurers using approaches allowable under current law and regulation.

This study makes several important contributions. First, most studies, and to our knowledge all studies of selection in automobile insurance markets, have lacked measures of private information that permit testing for whether the correlation results arise because of no asymmetric information between insurers and consumers or multidimensional private information. Ours is the first study of such markets to have direct measures of private information and is richer in private information than previous studies of selection in any insurance market.

Finkelstein and McGarry (2006) have one measure of the subjective probability of nursing home admission in their analysis of selection in the market for long-term care insurance. The study most similar to ours in having more than one private information measure is Fang, Keane, and Silverman (2008), a study of the supplementary Medicare insurance (Medigap) market. They measure financial risk preference, cognitive ability, health behaviors, and subjective risk, but we have these and additional measures of private information. The authors find evidence of advantageous selection in Medigap, but risk preference is not a determinant of insurance choice as economic theory would usually predict. In their study, cognitive ability, measured as we do, drives their negative correlation between insurance coverage and claims risk.

Second, our data allow us to measure risk preference more comprehensively than previously. Risk preference may not be stable across domains, but may be context-specific (e.g., Einav et al. 2012). We leverage the multiple ways in which our survey elicited preferences, personality traits, and beliefs to obtain a more general risk preference measure than in previous studies. Third, using our survey, we implement a novel method for quantifying moral hazard, which allows us to separate insurance policy choice from moral hazard. Fourth, given that we can identify respondents' insurers, we examine sorting by insurers of varying quality based on the objective risk of an accident.

Section II describes key institutional features of the U.S. automobile insurance market. Section III describes basic features of our survey. Section IV focuses on the role of private information in the automobile insurance market—particularly relationships between

²Abbring, Chiappori, and Pinquet (2003) is a notable exception—the authors use panel data to test for negative state dependence as a measure of moral hazard. They do not find evidence of moral hazard in the French automobile insurance market.

individuals' subjective probabilities of being involved in an automobile accident in the next year and 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 objective and unobserved 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 market reflects financial externalities of such insurance (e.g., absent third-party insurance, accident victims may not recover their losses), perceived consumer ignorance of insurance policy attributes, 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 are understandable to consumers. The notion of driving as a right has provided a rationale for premium regulation, community rating, take all comers, guaranteed renewability 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.

In the U.S., mandatory liability insurance coverage is nearly universal if one includes financial responsibility laws. Liability insurance is often the most practical option for drivers in states with financial responsibility laws. The requirement that drivers purchase minimum amounts of liability insurance prevents unraveling of contracts offering such minimum coverage, which has sometimes occurred in other insurance markets, e.g., health insurance (Cutler and Reber 1998). Even though most drivers are, in effect, required to carry liability insurance, some insurers may not insure high-risk drivers. In all of the four study states except North Carolina, insurers can refuse to write coverage. Of our study states, only North Carolina has a reinsurance facility. 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.³ Pennsylvania, Washington, and Wisconsin utilize an assigned-risk plan. These plans also require all automobile insurers to participate. In addition, there is optional automobile insurance coverage, e.g., first-party (collision) insurance. Insurance applications require basic demographic information including location, age, gender, race, and marital status. However, in some states, these are protected categories. 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, e.g., annual mileage, vehicle specifications or use. The driving record of an insured driver is an important information source on driver risk.

³Although 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. But with sorting on objective risk of an accident, which we argue exists below, insurance agents effectively decide on the risk levels of their clientele and hence on the shares of customers who are insured by a reinsurance facility.

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

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. The other study states regulate surcharges, but do not require specific schedules.

III. Data

Battelle Memorial Institute conducted a two-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). Questionnaire design was guided by questions from prior surveys. This study relies on data from both waves. Wave 1's first part, administered by telephone, included questions on: demographic characteristics/income/wealth; alcohol consumption; accident/traffic violation history; and altruism. Wave 1's second part, administered by computer about a month later, elicited information for which visual displays are helpful or questions involving detailed scenarios (e.g., for eliciting risk preferences, willingness to pay), and details about the respondent's automobile insurance policy. Wave 2, administered by computer, was conducted about a year after Wave 1.

Eligibility for the SAD required respondents to have driven and to have consumed alcohol during the last month, to reside within a study city, and to be age 18+. The recruitment process oversampled persons who consumed large amounts of alcohol in order to study drinking and driving decision-making and behaviors in detail. 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. Mean age of study participants is 43.8. Mean educational attainment is 15.6 years, substantially above the U.S. average. Mean household income is \$81,470, also above average. Over half are female (54.6%); 13.1 percent are non-white, and 46.6 percent are married.

IV. Private Information, Insurance Contract Choice, and Accidents

A. Overview

We first assess the role of private information on (1) individuals' choices of automobile insurance coverage, (2) their accident risks, and (3) the correlation between the two. Like Finkelstein and McGarry (2006), we divide information sources into three categories: (1) information insurers use in risk classification and thus in premium-setting; (2) information insurers often elicit from consumers but specifically used in risk classification; and (3) private information unavailable to insurers. We examine private information about risk preference in financial, driving, and health domains, cognitive ability, impulsivity, altruism

toward non-family members, and subjective beliefs about the probability the person will engage in reckless driving in the next year—speeding and drinking/driving. The goal is to determine which sorts of private information explain subjective beliefs about the probability of having an accident in the next year, observed insurance purchases, and ex post accident rates.

The system of equations is recursive. Objective information about individuals known and used or known and not used by insurers and information privately held by individuals affect objective and subjective probabilities about having an accident next year. Based on the objective risk of an accident, individuals are offered insurance policies at a premium for next year. Individuals select an insurer and policy from that insurer based on their preferences, private information, insurance policy characteristics and premiums. Once insurance coverage is selected, the individual forms subjective probabilities about her driving behaviors during the policy year. The individual then engages in actual behaviors that affect her accident record during the policy year. At year end, the accident record for the policy year are recorded ex post.

B. Three Types of Information

B.1. Type 1: Objective Factors Used by Insurers in Premium Setting—Accident determinants used by insurers for risk classification fall into these categories: demographic characteristics; driving attributes; driving history; and city. In our analysis of objective factors, demographic characteristics are: male < 25; female < 25; and currently married. For driving attributes, we include binary variables for whether the person reported driving 15,000+ miles/year and age, type, and use of primary vehicle—sedan, sport car, SUV, minivan, truck, or other—whether the person reports driving to work, and driving a motor vehicle regularly for a job. Driving history includes the number of: citations for speeding; arrests for DWI; and prior accidents. The SAD measured accidents at Waves 1 and 2. At Wave 1, the SAD obtained a self-report of the number of speeding citations, DWI arrests, accidents in the prior three years. One year later, the SAD obtained a self-report of accidents since Wave 1. Between Waves 1 and 2, 8.9 percent of respondents reported having had an accident; 21.1 percent reported having had an accident in the past three years at Wave 1.

First, to determine the relationship between actual accident risk and information used by the insurer for risk classification, we estimate:

$$Prob(Accident_k = 1 \mid X_{t-1}) = \Phi(X_{t-1}'\alpha), \quad (1)$$

where *Accident* is 1 if the person was involved in an accident in the past three years; X_{t-1} is a vector of characteristics used by insurers for risk classification. Alternatively, *Accident* is 1 if the person was involved in an accident in the year between Waves 1 and 2, and the number of accidents in three years prior to wave 1 is included as covariate in X_{t-1} . Thus, k may be $t-1$ or t .

Table 1 reports results for the two dependent variables. Both regressions include covariates for car age and characteristics and city, not shown. In the first specification, young drivers, male and female, those who drive 15,000+ miles/year, and have speeding citations and DWI arrests in the prior three years have higher probabilities of having had an accident in the three years prior to Wave 1. Persons currently married are less likely to have had an accident. In the second specification, the number of accidents in the past three years before Wave 1 has a positive effect on the probability of having had an accident between Waves 1 and 2. Having an accident in the past three years before Wave 1 leads to a 0.071 increase in the probability of having an accident in the years between Waves 1 and 2—a large effect size relative to the observational mean, 0.089. The coefficient for drives for work is also significant. Effect sizes are lower when the dependent variable is for one rather than three years; fewer coefficients are statistically significant at conventional levels in the second specification.

B.2. Type 2: Attributes Observed by Insurers but Not Used in Premium Setting—Attributes often observed by insurers but not used in risk classification are income and/or wealth, educational attainment (in years), and race/ethnicity.

B.3. Type 3: Multiple Dimensions of Private Information—The SAD elicited several dimensions of private information. The SAD used a sequence of hypothetical gambles over percent changes in lifetime income, derived from the Health and Retirement Study (HRS), to measure financial risk tolerance (Barsky et al. 1997). Based on the responses, we group respondents into three mutually exclusive categories—least, moderately, and most financially risk tolerant.

The series of (standard gamble) questions about risk-taking in the medical domain in SAD is: “We want you to keep imagining that you have gotten into an auto accident that leaves you paralyzed. Suppose that doctors could cure you of the paralysis by performing an operation. Without the operation, you would be paralyzed for the rest of your life. But if the operation went well, you would be completely cured of your paralysis. If the operation did not go well, you would die immediately without any pain. Would you choose to have the operation if the chance of dying was (a randomly selected value)?” The initial probability making the person indifferent between having and not having the operation was randomized. The computer program elicited probabilities according to pre-specified formula using the randomly-selected value as the starting value until the change in subjective probabilities fell below a threshold.

Impulsivity is a general term describing a tendency to act on a whim, disregarding a 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 impulsive individual may recognize that she is likely to act on a whim in the future, thus exposing her to a higher probability of personal harm (Sloan et al. 2013). A parallel is the sophisticate in the literature on self-control (Gruber and Köszegi 2001). To measure impulsivity, the SAD incorporated questions developed by Loewenstein et al. (2001).

Insurers know the individual's prior accident and arrest records, but the individual is likely to know more about her quality of driving and precaution levels than reflected in her 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 Wave 1 elicited the individual's subjective probabilities of speeding 15+ miles/hour over the speeding limit and of driving at least once after having too much to drink in the next year.

We use factor analysis to create an aggregate measure of risk preference based on: preferences for risk in financial and medical domains; impulsivity; whether the individual smokes currently; and whether the individual has ever used illicit drugs or licit drugs without a prescription. The factor analysis yields two factors with eigenvalues over 1. We use the first factor, which loads heavily on impulsivity, smoking, and drug use. Higher values imply higher risk preference.

Cognitive ability may affect the individual's ability to weigh potential benefits and costs of specific choices (Fang, Keane, and Silverman 2008) and/or accuracy of a person's subjective beliefs. The SAD measured recall, memory, and numeracy based on questions from the HRS. We aggregate these measures to create an index that ranges from 0–16, increasing in cognitive ability.

In feeling hopelessness, depression may increase subjective beliefs about probabilities of adverse events occurring (Hepburn, Barnhofer, and Williams 2009). If depression increases subjective probabilities of an accident arising from careless driving, it may increase her precaution. But, it may also lessen the individual's belief in ability to control one's fate, which may have the opposite effect (Zhang and Sloan 2014). The SAD measured depression with questions from the SIG-E-CAPS, a depression screening tool (Guck et al. 2003; Lieberman 2003; Wise and Rundell 1994). The SAD included nine symptoms; we measure depression as a count of symptoms the respondent experienced during the year before Wave 1.

Persons who are more altruistic, especially about harming strangers, may be safer drivers and hence less accident-prone. The SAD made statements relative to altruism toward non-family members, none of which reference alcohol consumption or driving while intoxicated. *Cet. par.*, we expect more altruistic persons, i.e., who internalize the externalities involving harm to others, to be more careful drivers. The SAD included nine statements dealing with altruism without referring to family members, each with three response options—disagree, neutral, agree. We create an altruism index by assigning each response a value of 1 to 3, where 3 is the most altruistic, and sum across questions.

Persons placing a lower value on avoiding injury and/or disability should be less cautious. The SAD included 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 previously (Sloan et al. 1998; Perreira and Sloan 2002; Khwaja, Sloan, and Wang 2009).

To elicit maximum willingness-to-pay, respondents were asked to compare two areas: Area A with has the same monthly cost of living as the place where the person currently lives and is assumed to have a 0.01 probability of a person getting into an automobile accident per year that results in the person becoming paralyzed. Area B has a \$X higher cost of living and a 0.008 probability of being involved in an automobile accident resulting in the person being paralyzed. To avoid starting point bias, SAD assigned random starting values of \$X. Based on several rounds of questions, we derive a final value for avoiding a 0.002 per year probability of becoming paralyzed. Finally, the SAD elicited subjective probabilities of speeding 15+ miles/hour over the speed limit, drinking and driving, and having an accident next year. We include subjective probabilities elicited at Wave 1 as additional sources of private information.

Table 2 analyzes the same dependent variables as Table 1, but adds explanatory variables for attributes of insured individuals known but not used by insurers (Z_{t-1}) and for private information (PI_{t-1}), all at Wave 1, to assess determinants of the probability of an accident from the insurer's perspective if there were no information asymmetries and insurers used all information currently available to them. We also estimate a more parsimonious model containing only two explanatory variables for PI_{t-1} .

$$Accident_t = \kappa_0 + \kappa_1 X_{t-1} + \kappa_2 Z_{t-1} + \kappa_3 SubjProbAccident_{t-1} + \kappa_4 RiskPref_{t-1} + \nu_t. \quad (2)$$

The dependent variable is a binary variable for whether the person had an accident in the year after Wave 1. The parameters κ_2 and κ_3 relate private information about risk preference and the subjective probability of an accident to actual accident occurrence next year. For both types of private information to be relevant to insurers, $\kappa_2 \neq 0$ and $\kappa_3 \neq 0$. We also expect $\kappa_1 \neq 0$, i.e., objective risk as of period $t-1$ predicts actual accident occurrence in t .

The coefficients on characteristics used by insurers in Table 2 are very similar to their Table 1 counterparts. The coefficients are robust to substantial changes in specification (compare cols. 2 and 3 and 4 and 5). Adding information collected but not used by insurers and individual's private information in Table 2 adds 0.03 to 0.04 to the R^2 s in Table 1, which implies that consumers possess some information which would improve accuracy in predicting future accident probabilities if insurers had the information and actually used it.

When the dependent variable is a binary for having an accident in the last three years, higher net worth drivers have a lower probability of an accident, but, *cet. par.*, more highly educated persons and non-whites have a higher probability on average. Among variables for private information, coefficients on self-assessed driving ability—worse self-assessed driving ability leading to more accidents and for risk preference—more risk tolerant persons being more likely to have an accident are highly significant. A one standard deviation increase in risk preference, i.e., becoming substantially more risk tolerant, would lead to a 0.044 increase in the accident probability in a three-year period, slightly over 20 percent of the corresponding observational mean. The coefficients for the subjective probability of an accident are positive and nearly statistically significant when the dependent variable is any accident in the

last three years ($p=0.091$, col. 2, $p=0.069$, col. 3). When the dependent variable is a binary variable for having had an accident between Waves 1 and 2, the coefficient on the subjective probability of an accident next year, recorded at Wave 1, is estimated very imprecisely. But given the stochastic property of accidents, an accident history for a year represents much less information about the underlying quality of driving than a three-year period does.

C. Subjective Probability of an Accident in the Next Year

Specification—The subjective probability of an accident is based on (1) information used by insurers; (2) other information available to insurers but not used; and (3) private information. To examine the relationship between the subjective probability of an accident next year and specific sources of private information, conditional on objective information used and not used by insurers, we estimate:

$$\text{Subj. Prob. Accident}_{t-1} = \beta_0 + \beta_1 X_{t-1} + \beta_2 Z_{t-1} + \beta_3 PI_{t-1} + \varepsilon_{t-1}. \quad (3)$$

All variables come from Wave 1. Measures of X_{t-1} are the predicted probability of having an accident in the past three years elicited at Wave 1 based on Table 1 coefficients and a binary variable for actually having had an accident during the same three years. Measures of Z_{t-1} and PI_{t-1} are the same as in Table 2.

Results—Overall, there are several statistically significant and plausible relationships between the subjective probability of having an accident next year and other types of objective and private information. The subjective probability of an accident reflects the objective probability of having had an accident during the three years prior to Wave 1. Net worth (for Z_{t-1}) negatively affects the subjective probability. Self-assessed driving ability negatively affects the subjective probability of an accident, and the two subjective probabilities of reckless driving both have positive effects (for PI_{t-1}). Although positive, the coefficient on risk preference is not statistically significant, which suggests that although risk-tolerant persons are more accident prone, such persons on average do not think that they have a higher accident risk. A one unit change in the factor (approximately the standard deviation of the risk preference factor), results in less than a 0.01 change in the subjective probability of having an accident next year.

In sum, the subjective probability of an accident reflects information known and used by insurers in underwriting and premium-setting, some other information known to insurers, and private information. The next step is to determine the extent to which private information affects insurance choice.

D. Choice of Insurance Coverage

At Wave 1, the SAD asked whether the person had liability insurance, and if so, what the liability limits were. Liability limits measure quantity of liability insurance purchased. A 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), which should decrease lower-income households demand on insurance. But as seen above,

wealthier persons have lower objective and subjective accident risk, i.e., exercise self-protection given their greater financial exposure (Ehrlich and Becker 1972). Also for this reason, we expect the individual's choice of liability limits to depend on wealth. If richer individuals are less risk averse, demand for insurance would decrease, *cet. par.*

To measure private information, we include covariates for risk preference and the subjective probability of having an accident next year elicited at Wave 1. Although, as seen in Table 3, risk preference at most has a minimal effect on subjective beliefs of an accident, risk preference is key to the individual's insurance purchase decision. We estimate:

$$LiabLimit_{t-1} = \gamma_0 + \gamma_1 X_{t-1} + \gamma_2 NetWorth_{t-1} + \gamma_3 PI_{t-1} + \eta_{t-1}. \quad (4)$$

We base the empirical specification of eq. (4) on variables for which the theoretical case for inclusion is greatest. The dependent variable is based on the higher reported liability limit. The liability limit is set to 0 for the 39 persons who lacked liability insurance. For private information, we use the subjective probability of an accident and our risk preference measure, which is decreasing in risk aversion. For X_{t-1} , we use the predicted objective probability of an accident next year (from eq. 1) and the binary variable for whether the individual actually had an accident during the three years before Wave 1. The coefficients estimates for X_{t-1} are jointly insignificant ($p=0.399$), reflecting higher premiums for higher objective accident risk, and possibly sorting on objective risk.

The coefficient on net worth is positive and statistically significant, indicating that wealthier persons demand deeper liability coverage. Each additional \$100k increase in net worth leads to an \$8,100 increase in the upper liability limit, much lower than the “rule of thumb” to carry liability coverage at least equal to total assets.⁴ The coefficient of interest is γ_3 , which measures the effect of an individual's private information on insurance coverage. The classic model of unidimensional asymmetric information about risk type implies that an individual with a higher subjective probability of an accident will choose more complete insurance. With multidimensional private information, more risk-averse individuals may choose more complete insurance while having a lower accident risk.

Conditional on objective risk, we find a statistically significant negative relationship between risk preference and liability limits (Table 4, cols. 5 and 6) and risk preference and having collision insurance (col. 7) —more risk-averse persons demand more insurance. But risk preference has no effect on whether the person has collision insurance with a deductible of \$500 or less (col. 8). The subjective probability of an accident has no statistically significant influence on liability limits or on collision coverage.

In sum, private information, particularly risk preference, and net worth, affect individuals' insurance choices. The importance of this finding depends on whether this private information also predicts *ex post* accident risk, but as we saw in Table 2, more risk-tolerant

⁴<http://guides.wsj.com/personal-finance/insurance/how-much-car-insurance-do-you-need/>, accessed 3/19/15.

persons at Wave 1 have a higher probability of reporting having had an accident ex post, i.e., at Wave 2.

E. Private Information and Ex Post Accident Risk: Positive Correlation Test

Together, Tables 2 and 4 suggest advantageous selection. Although we consider many possibilities, other dimensions of private information may not be captured by our measures of PI_{t-1} . For this reason, and to compare our results with previous studies, we perform a positive correlation test. The positive correlation test does not require observing private information. Yet, results of this test may be misleading if there are offsetting sources of information that yield a zero correlation (Finkelstein and McGarry 2006).

We use probit to estimate parameters of a model of accident occurrence—a function of insurance coverage—controlling for risk classification, similar to Finkelstein and Poterba (2004):

$$\text{Prob}(Accident_t = 1 \mid X_{t-1}, Insurance_{t-1}) = \Phi(\theta_1 X_{t-1} + \theta_2 Insurance_{t-1}), \quad (5)$$

where *Insurance* refers to insurance policy characteristics. With asymmetric information only about risk type, $\theta_2 > 0$, and with asymmetric information only about risk preference (unobserved by insurers), $\theta_2 < 0$. With multidimensional, offsetting private information, we may find $\theta_2 = 0$.

The results show a zero correlation between insurance coverage and accident risk (Table 5). The zero correlation could mask a combination of advantageous selection, a phenomenon leading to a negative correlation, and moral hazard, leading to a positive correlation (de Meza and Webb 2001). Hence, we develop a method for separating selection from moral hazard.

V. Separating Plan Selection from Moral Hazard

A. Overview

We use questions from Waves 1 and 2 that elicit how individuals' subjective probabilities of reckless driving change in response to changes in financial penalties imposed by the insurer for a traffic violation. Our survey randomized financial penalties for each respondent. We use these results in combination with relationships between subjective probabilities of reckless driving and actual realizations of reckless driving, and between reckless driving and ex post accident risk, to quantify moral hazard. Our approach involves three steps.

B. Step 1. Relationship between Expected Premium Increase and Subjective Probability of Reckless Driving

We first relate an individual's subjective probability of reckless driving, measured alternatively by the probability of speeding given his expected penalty from speeding and driving after having had too much to drink. The SAD asked respondents to estimate the (subjective) probability of speeding next year and the premium increase conditional on being

convicted for speeding The SAD then posed two scenarios in which the expected premium was increased by a randomized amount and elicited new (subjective) probabilities of speeding. Since respondents were asked to state subjective probabilities of engaging in reckless driving next year in response to randomly-selected penalties presented successively at each wave, respondents may have selected a lower probability of reckless driving in response to an increase in the expected penalty posed by the survey just to give a logically plausible response. The same sequence of questions but with different randomly-selected values was posed in both survey waves. To eliminate this potential source of bias, for each individual we randomly select one expected premium increase-probability of reckless driving pair from each of the two waves, based on the assumption that respondents could not remember their precise Wave 1 responses at Wave 2. We then estimate the following equation with individual fixed effects and standard errors clustered at the individual level:

$$SubjProbSpeeding_t = \phi_0 + \phi_1 E_t[\Delta Premium \mid Speeding] + \psi_t, \quad t \in \{-1, 0\}, \quad (6)$$

where $E_t[\Delta Premium \mid Speeding]$ is the expected change in premium conditional on speeding 15mph. The coefficient of interest is ϕ_1 , the mean individual change in the subjective probability of speeding due to a given percent increase in premiums. The null hypothesis is $\phi_1 = 0$ —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 next year given the person's subjective belief about a DWI conviction. Respondents were also asked the probability of drinking and driving if the expected premium increase doubled. We randomly select one pair of responses from each wave and follow the same approach as for the speeding scenarios to estimate eq. (6) with *Drinking and Driving* replacing *Speeding*.

The relationship between the change in expected premiums and in the subjective probabilities can be interpreted as causal for two reasons. The first is the randomization of the hypothetical changes by SAD in expected premium increases following a conviction for speeding or drunk driving (randomized because the probability of being pulled over by police conditional on speeding or drunk driving was randomized). Second, we include individual fixed effects, which account for time-invariant heterogeneity in formation of subjective beliefs.

C. Step 2. Relationship between Subjective Probability of Reckless Driving and Actual Reckless Driving Behavior

Step 2 measures the relationship between the subjective probability of reckless driving and realizations of reckless driving. We regress the number of times an individual reports having driven after drinking too much during the past year at Wave 2 on the subjective probability of driving after drinking too much during the next year at least once from Wave 1. We lack a measure of actual speeding behavior from Wave 2. We assume that the subjective probability of speeding is accurate; the coefficient in this step is set to 1, assuming that individuals are rational in their subjective beliefs about future speeding.

D. Step 3. Relationship between Reckless Driving and Ex Post Accident Risk

Third, we measure the relationship between actual reckless driving behavior and the ex post probability of an accident. We use probit to estimate the probability of any accident realization as a function of whether an individual drove after drinking too much in the same year.⁵ We also use probit to estimate the probability of any accident realization during the year before Wave 2, as a function of the subjective probability of speeding next year reported in Wave 1, again assuming that the subjective probability of speeding next year at Wave 1 equals the actual probability of speeding during the year before Wave 2.

E. Results

Descriptive statistics are shown in the Appendix (Table A1)⁶ In Step 1, doubling the expected premium increase from a conviction for speeding leads to a 0.33 lower subjective probability of speeding 15+ mph during the next year (Table A2, row 3, col. 7), and doubling the expected premium increase from drinking and driving leads to a 0.089 lower subjective probability of drinking and driving (Table A2, row 4, col. 11). In Step 2, the change in the objective probability of reckless driving from a change in the subjective probability is assumed to be 1 for speeding and is estimated to be 0.693 for drinking and driving (Table A3, row 1). In Step 3, the change in the objective probability of an accident due to a change in the objective probability of reckless driving is 0.046 for speeding and 0.048 for drinking and driving (Table A3, rows 2 and 3).

The product of the estimates from these steps for speeding is -0.015 , or -16.9 percent relative to the sample mean objective probability of having had an accident, and for drinking and driving it is -0.003 , or -3.4 percent relative to the sample mean (Table 6). Moral hazard, particularly for speeding, is non-trivial.

Alternatively, in sensitivity analysis, we take 100 random draws of stated changes in speeding and drinking-driving behaviors in response to changes in premium penalties imposed for reckless driving responses to the hypothetical change in the premium for engaging in/being pulled over for/convicted of reckless driving. The estimates are robust to changes in the method used for computing the effect of engaging in reckless driving on insurance premiums (Table A2). In addition, we perform robustness checks of Step 3 by adding/dropping binary variables for city and alternatively including individual fixed effects. The parameter estimates do not change much and do not alter our conclusions on moral hazard. Underlying the use of individual fixed effects is the assumption that other behaviors (e.g., texting while driving, drag racing) correlated with speeding or drunk driving are time invariant. If these other behaviors potentially affecting accident risk are time-varying *and* covary⁷ with the behaviors observed by SAD, the Step 3 result is not interpretable as a causal effect.

⁵We pool observations from both waves and include a wave fixed effect to account for the fact that in wave 1 counted accident realizations from the past three years and Wave 2 counted accidents from the past year. We also cluster standard errors at the individual level.

⁶Appendix Table A1 and other tables at <http://sites.duke.edu/jriapr14046r2appendix/?p=2>

⁷We also include a wave fixed effect in specifications with individual fixed effects. This covariate should account for time-varying behaviors unrelated to the attributes of reckless driving we measure.

F. Summary

Individuals possess private information about their driving abilities, risk preference, and beliefs about their precaution levels next year, which are systematically and plausibly related to their subjective probabilities of having an accident next year. Private information about risk preference affects demand for insurance and accident risk. Our results imply advantageous selection, particularly in level of liability coverage. But, the positive moral hazard effect offsets advantageous selection, consistent with our result from the correlation test.

VI. Sorting of Policyholders Based on their Accident Risk

A. Rationale for Sorting

Our finding of advantageous selection is surprising, especially given state governments' role in regulating terms of the sale of automobile insurance. State laws and regulations prohibit insurers from using all information they possess. State laws limit underwriting. Laws mandating insurance coverage work to combat adverse selection, but such laws disproportionately attract high-risk persons willing to bet that if sued, they would be declared judgment proof.

Thus far, we have focused on the demand side. Insurers are not passive agents; even within the law they can affect outcomes through underwriting, marketing practices, and policy design. One way automobile insurers can combat potential adverse selection and its effects is through sorting, as explained below.

Rejections of applications for automobile insurance are rare. Only 2.2 percent of SAD respondents had been rejected by an insurer in the last three years at Wave 1; only 1.7 percent were rejected in the year before Wave 2. Very few respondents were covered by surplus-line insurers or high-risk pools. This suggests that there must be another mechanism for insuring high-risk drivers.

A mechanism for dealing with high-risk drivers is for insurers to sort drivers based on factors associated with future accident risk; 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, fewer repair firms in the insurer's network, and less access to the loaner vehicles. By specializing, lower-quality insurers become expert in gauging not-easily observed consumer characteristics. Methods for sorting include adjusting the content of advertisements (e.g., emphasis on specializing in insuring drivers with bad driving records or bad credit), office location, and simply welcoming prospective customers in the risk class in which the insurer specializes.

Our empirical analysis of sorting in the automobile insurance market involves three steps. In Step 1, we show that higher-risk drivers measured on objective characteristics used by insurers for risk classification tend to be covered by lower-quality insurers. Estimating parameters of a hedonic premium equation in Step 2 reveals that premiums *fall* with increases in consumer ratings of insurers (excluding consumer satisfaction with premiums).

Absent some sort of non-price rationing, one would expect price and quality to be positively related. In Step 3, we investigate whether high-risk drivers possess more private information about their accident risk. If so, this could explain why premiums paid by the high-risk group are disproportionately high in Step 2.

B. Choice of Insurer

We obtain data on insurers from three additional sources: J.D. Power, Insure.com, and *Consumer Reports*. Each source reports consumer ratings on multiple dimensions of quality for large automobile insurance companies. Insure.com also reports coverage options and discounts offered by each insurer included in its study. Consumer ratings reported in these studies cover 83 percent of our sample for J.D. Power ratings and 77 percent of our sample for *Consumer Reports* and Insure.com ratings. *Consumer Reports* publishes automobile insurance ratings based on a survey of 102,207 subscribers. The “reader score” measures overall satisfaction with claims handling based on the subsample of 29,116 survey respondents with a claim, 2009 to mid-2012. Scores range 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. “Premium satisfaction” is on a scale 1–5, increasing in satisfaction. Insure.com published ratings of 20 large automobile insurance companies based on a survey of 5,600 insurance customers conducted in 2012. The “overall score,” ranging from 0–100, is an aggregate measure of satisfaction with: claims processing; customer service; premium paid given the coverage; the percent of respondents who would renew their coverage (“plan to renew”); and the percent of respondents who 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 respondents bought from the company (e.g., “saw commercial”). J.D. Power ratings include: (1) “overall claims satisfaction,” (2) “overall purchase experience,” (3) “claims service interaction,” based on claimants’ ratings of the insurer representative or agent handling the claim, and (4) “local agent interaction,” reflecting purchasers’ experiences interacting with the insurer’s local agent or staff. All ratings vary from 2 to 5, with 5 among the best, 4 better than most, 3 average, and 2, the rest.

Given that private information affects individuals’ choice of level of insurance coverage, 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 estimate:

$$Attribute_{t-1} = \pi_0 + \pi_1 X_{t-1} + \pi_2 PI_{t-1} + \omega_{t-1}, \quad (7)$$

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. If $\pi_1 \neq 0$, then the observable accident probability, measured by the predicted objective accident probability in the last three years before Wave 1 and a binary for having actually having had an accident during this period, is related to the attribute represented by the

dependent variable, which suggests sorting by accident risk along that dimension of insurer quality. If $\pi_2 \neq 0$, then individuals' residual private information also affects choice of insurer.

An individual with a higher predicted objective probability of an accident is more likely to have a low-quality insurer, as measured by summary indicators of quality (Table 7, Panel A, cols. 2, 8, and 10). The coefficients on the binary for actual accidents vary in sign and are uniformly smaller than their associated standard errors, but the coefficients on the two components of X_{t-1} are jointly significant for the reader score, overall purchase experience, and plan to renew—in all these cases implying the persons with higher accident risk tend to obtain coverage from lower-quality insurers.

Policyholders with a higher objective accident probability and a prior accident record are less likely to be satisfied with their premiums (Panel B, col. 2), which is plausible since such persons are likely to pay higher premiums on average. But the effect is partly offset by higher satisfaction with premiums among policyholders with private information that they are more likely to be involved in an accident. The negative coefficient on the risk preference factor implies that premium satisfaction decreases as risk tolerance increases.

Persons with high objective accident probabilities are much more likely to be influenced by insurers' advertisements (Panel B, col. 10). Not only do persons with a higher objective risk face higher premiums, which would encourage search, but they are also likely to be less welcome by insurers when they seek to purchase coverage. Friends might be reluctant to encourage an accident-prone friend to buy coverage from their insurer. As expected, accident-prone persons are more likely to be satisfied with accident forgiveness (Panel B, col. 8) because they are more likely to have had their accidents forgiven. In Panel C, the dependent variable is a consumer satisfaction index reflecting all of the satisfaction measures available for the respondent's insurer excluding premium satisfaction. Like Panel A, persons with a higher objective accident probability and with a prior accident have lower assessments of overall insurer quality. Neither private information covariate has a statistically significant impact.

Taken together, these findings suggest that more accident-prone persons, measured by factors that insurers consider, are less satisfied with their insurers, even on dimensions other than the premium. Proportions of high- and low-risk drivers are systematically related to the quality of the insurer.

C. The Effect of Insurer Quality on Premiums Paid

Cet. par., maximum willingness to pay for a good or service should be increasing in the good or service's quality. Failure to find this relationship empirically may reflect some type of non-price rationing, in this context sorting by insurers based on the person's objective probability of an accident. We estimate:

$$Premium_{t-1} = \tau_0 + \tau_1 X_{t-1} + \tau_2 InsCoverage_{t-1} + \tau_3 InsQuality_{t-1} + \xi_{t-1} \quad (8)$$

In eq. (8), the annual premium paid by the SAD respondent for the household's automobile insurance policy depends on the objective accident risk, insurance contract parameters—the upper liability limit (in \$100,000s), a binary variable for whether the respondent had collision coverage, and insurer quality, the same measure as in Table 7, Panel C; insurer quality and other factors. All specifications use a Heckman correction to account for sample selection, i.e., for whether or not the respondent had liability insurance.

In Table 8, col. 1, based on the full sample, as expected, premiums rise with increases in the predicted objective probability of an accident and the binary variable for an accident in the three years before Wave 1. Premiums are higher for persons with collision coverage and higher liability limits, although the latter is not statistically significant. Higher quality insurers have lower premiums, evidence for sorting. Results for other covariates are generally plausible but not shown.

Next we stratify the sample based on terciles of the predicted objective probability of an accident. We remove observations with an accident in the three years before Wave 1 if they are in the low-risk or medium-risk tercile and place them in a fourth group—low or medium risk and accident. The fourth group contains relatively few individuals. The high-risk group contains individuals with high predicted accident risk and an accident if an accident was reported.

Two results are particularly noteworthy. First, persons in the high-risk group pay high premiums for higher liability limits. The parameter estimates for upper liability limit for the other three groups are not statistically significant. Second, the coefficients on insurer quality are negative for most groups, but only statistically significant in the low-risk/no accident and low- or medium risk/accident analyses. The latter result implies that lower-risk drivers do not pay higher premiums for having had an accident in the past three years.

D. Private Information by Risk Type

Thus far, we have seen that persons with higher objective probabilities of an accident tend to purchase automobile insurance from firms assessed by consumers to offer poorer quality of service. Premiums obtained by firms with lower assessed quality charge higher, not lower premiums. Both findings suggest sorting. Hendren (2013), using data from other types of insurance, found that high-risk persons possess more private information than low-risk types do. If so, high-risk drivers based on factors observed and used by insurers are less desirable customers. Thus insurers must be compensated for this in some way.

As a final step, we explore a possible reason for insurer sorting based on accident risk. We hypothesize that high-risk persons, based on their objective probabilities of an accident and actual accident histories, possess more private information about their actual riskiness than others. To gauge the importance of private information for persons with different objective accident risk, we re-estimate eq. (3) with the sample split into the same risk groups as in the previous section. The dependent variable is a binary for whether or not the respondent had an accident between Waves 1 and 2.

Examining mean values by risk group (Table 9), the mean fractions of persons with an accident in the follow-up year rises monotonically from the low-risk/no accident group to the low- or medium-risk/accident group. The fractions of persons with an accident during follow-up for the high-risk and low-or medium-risk/accident group are statistically different from the low-risk no accident group. Risk tolerance rises monotonically from the low-risk/no accident to the low- or medium-risk/accident group. The subjective probability of an accident is statistically higher for the high-risk and low-or medium-risk accident group than for the low-risk/no accident group. Persons in the low- or medium-risk/accident group are far more risk tolerant than those in the low- and medium-risk groups who did not have an accident in the three years prior to Wave 1.

In regression analysis with the dependent variable a binary variable for whether or not the person had an accident in the year before Wave 2, the only statistically significant result for the high-risk group is for the subjective probability of an accident, where the marginal effect is 0.258. Among the other measures of private information, the marginal effect of risk preference is 0.040 and statistically significant in the regression for the low-risk/no accident group. Since the marginal effect applies to a factor for which units have no natural meaning, consider that the difference between the means on risk preference between low-risk/no accident and the high-risk group is -0.272 . Multiplying this mean value by the low-risk/no accident's marginal effect of risk preference yields 0.011, which is substantially below the marginal effect on accident risk from the subjective probability of an accident for the high-risk group, supporting the view that private information is relatively important among high objective risk consumers,⁸ which in turn should be reflected in premiums. However, the coefficient on the subjective probability of an accident for the medium-risk/no accident group is negative, implying that persons in this group were overly pessimistic about their future accident experiences.

Thus, overall from the evidence obtained from Step 3, we cannot conclude that high-risk persons possess more private information about their accident risk. Perhaps the results on premiums reflect insurers' beliefs about private information, which have not been sufficiently validated empirically. Or one year's experience is insufficient to measure individual driving quality.

VII. Discussion and Conclusion

Our empirical analysis yields these major findings. (1) Information insurers routinely collect on their customers predicts the objective probability of an accident during the policy year. (2) The subjective probability of an accident in the following year reflects the risk of an accident based on factors observed and used by insurers, but it also contains additional information not used by insurers in premium setting and underwriting. (3) Risk preference is an important source of private information. However, given that risk preference is multi-dimensional and may be domain specific, the overall effect of risk preferences on demand for insurance is an empirical question. Risk preference affects demand for insurance through

⁸For Tercile 2, the coefficient on the subjective probability of an accident is an implausible -0.210 , which may partially reflect multicollinearity with the objective probability of an accident. Note that the coefficient on the objective probability of an accident is implausibly high.

the traditional channel as a means of consumption smoothing; but, because risk preference also affects driving and other behaviors, risk tolerant persons may demand more, not less, insurance. In our empirical analysis, risk-tolerant persons have lower demand for liability insurance even after taking account of other dimensions of risk preference, providing evidence of advantageous selection. (4) The combination of advantageous selection and moral hazard is consistent with the zero correlation between insurance choices and ex post accident risk we obtain. (5) There is evidence of sorting of policyholders across insurers based on factors insurers use in underwriting/premium-setting. By sorting based on objective probabilities of an accident, people find themselves in pools with persons of similar accident risk. Since such sorting reduces premiums to low-risk drivers, they are understandably motivated to purchase deeper coverage.

According to the old adage, “If it ain’t broke, don’t fix it.” In the U.S. automobile insurance market, institutional responses by private firms have done the fixing.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1

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

	Mean (std. dev.) (1)	Any accident in last 3 years (Wave 1) (2)	Any accident in last year (Wave 2) (3)
<i>Dependent variables</i>			
Any accident in last 3 years (Wave 1)	0.212 (0.409)		
Any accident in last year (Wave 2)	0.089 (0.284)		0.071 *** (0.018)
<i>Demographic characteristics</i>			
Male <25	0.020 (0.139)	0.155 ** (0.074)	0.006 (0.059)
Female <25	0.041 (0.198)	0.102 * (0.056)	0.061 * (0.036)
Married	0.466 (0.499)	-0.061 ** (0.025)	-0.016 (0.018)
<i>Driving characteristics and history</i>			
Miles > 15k/yr	0.154 (0.362)	0.104 *** (0.030)	0.034 (0.021)
Drives to work	0.759 (0.428)	0.017 (0.029)	0.008 (0.021)
Drives for work	0.321 (0.467)	0.032 (0.026)	0.046 *** (0.017)
Speeding citations	0.523 (1.278)	0.027 *** (0.009)	0.003 (0.006)
DWI arrests	0.039 (0.299)	0.080 ** (0.040)	-0.057 (0.060)
N	1,172	1,171	1,155
Pseudo R-squared		0.06	0.07

Notes: Marginal effects; standard errors in parentheses

All regressions include car age and fixed effects for car type and city (not shown). All Explanatory variables other than accident in last year measured at Wave 1.

* p<0.10

**

p<0.05

p<0.01

Table 2

Objective probability of an accident based on characteristics used by individual drivers

	Mean (std. dev.)	Any accident in last 3 years (Wave 1)			Any accident in last year (Wave 2)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Dependent variables</i>							
Any accident in last 3 years (Wave 1)	0.212	(0.409)					
Any accident in last year (Wave 2)	0.090	(0.286)					
<i>Demographic characteristics, used</i>							
Male <25	0.020	(0.141)	0.191 ***	(0.074)	0.176 **	(0.074)	0.031 (0.058) 0.010 (0.059)
Female <25	0.041	(0.199)	0.109 *	(0.056)	0.124 **	(0.055)	0.064 * (0.036) 0.067 * (0.037)
Married	0.461	(0.499)	-0.034	(0.027)	-0.036	(0.027)	0.004 (0.019) 0.000 (0.019)
<i>Driving characteristics and history</i>							
Miles > 15k/yr	0.154	(0.361)	0.112 ***	(0.031)	0.111 ***	(0.030)	0.035 (0.021) 0.035 ** (0.021)
Drives to work	0.761	(0.427)	0.006	(0.029)	0.004	(0.029)	0.011 (0.022) 0.010 (0.021)
Drives for work	0.325	(0.468)	0.032	(0.026)	0.030	(0.025)	0.045 ** (0.018) 0.049 *** (0.018)
Speeding violations	0.521	(1.283)	0.026 ***	(0.009)	0.027 ***	(0.009)	-0.001 (0.006) 0.003 (0.006)
DWI arrests	0.039	(0.303)	0.068 *	(0.040)	0.066 *	(0.040)	-0.073 (0.067) -0.070 (0.065)
<i>Demographic characteristics and wealth, not used</i>							
Net worth (\$100k)	3.406	(5.989)	-0.004 *	(0.002)	-0.004 *	(0.002)	0.000 (0.002) 0.000 (0.002)
Education (years)	15.616	(1.940)	0.022 ***	(0.007)	0.024 ***	(0.007)	0.000 (0.005) 0.001 (0.005)
Non-white	0.130	(0.336)	0.073 **	(0.035)	0.063 *	(0.034)	0.033 (0.024) 0.030 (0.024)
<i>Private information</i>							
Driving: worse than others	0.023	(0.150)	0.208 ***	(0.076)			0.065 (0.044)
Driving: about the same as others	0.246	(0.431)	0.048	(0.033)			-0.041 (0.025)
Driving: better than others	0.493	(0.500)	-0.001	(0.030)			-0.003 (0.020)
Risk preference	0.003	(0.997)	0.044 ***	(0.013)	0.047 ***	(0.012)	0.017 * (0.009) 0.019 ** (0.008)
Cognitive ability (0-16)	14.474	(1.743)	-0.002	(0.007)			-0.002 (0.005)
Depressed (0-1)	0.182	(0.386)	-0.019	(0.032)			0.035 (0.021)
Altruism (non-familial)	22.994	(2.623)	-0.002	(0.005)			0.006 * (0.003)
WTP to avoid paralysis (monthly)	36.802	(33.929)	-0.000	(0.000)			0.001 *** (0.000)
Subjective prob. of speeding	0.449	(0.399)	-0.033	(0.032)			0.036 (0.023)

	Mean (std. dev.)	Any accident in last 3 years (Wave 1)		Any accident in last year (Wave 2)	
	(1)	(2)	(3)	(4)	(5)
Subjective prob. of drinking and driving	0.165	(0.292)	0.011	(0.042)	−0.022 (0.030)
Subjective prob. of accident	0.134	(0.145)	0.135 * (0.079)	0.142 * (0.078)	0.022 (0.056) 0.024 (0.056)
N	1,134	1,133	1,152	1,120	1,136
Pseudo R-squared		0.10	0.09	0.12	0.09

Notes: Marginal effects; standard errors in parentheses.

All regressions include car age and fixed effects for car type and city (not shown).

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

Table 3

Formation of subjective beliefs about the probability of an accident

	Mean (std. dev.) (1)	Subjective prob. of accident (2)
<i>Dependent variables</i>		
Subjective prob. of accident	0.135 (0.146)	
<i>Accident probability, used</i>		
Objective probability of accident in last 3 years (Wave 1, 0–1)	0.214 (0.105)	0.149 *** (0.043)
Any accident in last 3 years (Wave 1)	0.214 (0.410)	0.019 * (0.011)
<i>Demographic characteristics and wealth, not used</i>		
Net worth (\$100k)	3.415 (5.986)	−0.003 *** (0.001)
Educational attainment (years)	15.619 (1.939)	−0.001 (0.002)
Non-white (0–1)	0.129 (0.335)	−0.012 (0.013)
<i>Private information</i>		
Driving: worse than others (0–1)	0.022 (0.147)	0.104 *** (0.030)
Driving: about the same as others (0–1)	0.248 (0.432)	0.038 *** (0.012)
Driving: better than others (0–1)	0.493 (0.500)	0.031 *** (0.011)
Driving: much better than others (0–1)	0.238 (0.426)	
Risk preference	0.004 (0.997)	0.008 (0.005)
Cognitive ability (0–16)	14.476 (1.743)	−0.004 (0.003)
Depressed (0–1)	0.181 (0.386)	−0.019 (0.012)
Altruism (non-familial)	22.994 (2.621)	0.002 (0.002)
WTP to avoid paralysis (monthly)	36.758 (33.923)	0.000 (0.000)
Subjective prob. of speeding	0.450 (0.399)	0.024 ** (0.011)
Subjective prob. of drinking and driving	0.165 (0.292)	0.026 * (0.015)
Constant		0.090 (0.065)
N	1,135	1,135
R-squared		0.07

*
p<0.10**
p<0.05

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Table 4
Relationship between insurance coverage and subjective and objective probability of an accident

	Means (std. dev.)			OLS		Probit			
		Liability limit Has insurance	Has collision insurance Has liability insurance	Deductible <= \$500 Has collision insurance	Liability limit	Liability limit Has insurance	Has collision insurance Has liability insurance	Deductible <= \$500 Has collision insurance	
	Liability limit	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Dependent variables</i>									
Upper liability limit (\$100k)	2.943 (2.168)		3.067 (2.125)						
Has collision insurance (0–1)				0.917 (0.276)					
Deductible <=\$500 Has collision insurance (0–1)					0.837 (0.369)				
<i>Accident probability, used</i>									
Objective probability of accident in last 3 years (Wave 1)	0.209 (0.099)		0.209 (0.099)	0.214 (0.104)	0.210 (0.100)	–0.857 (0.694)	–0.972 (0.699)	–0.104 (0.075)	–0.180 (0.121)
Any accident in last 3 years (Wave 1)	0.213 (0.410)		0.213 (0.409)	0.214 (0.410)	0.215 (0.411)	0.289 (0.168)	0.267 (0.170)	0.033 (0.021)	0.003 (0.030)
<i>Wealth, not used</i>									
Net worth (\$100k)	3.738 (6.344)		3.833 (6.396)	3.509 (5.991)	3.821 (6.350)	0.081 (0.011)	0.078 (0.011)	0.021 (0.005)	–0.001 (0.002)
<i>Private information</i>									
Risk preference	–0.054 (0.958)		–0.093 (0.925)	–0.033 (0.972)	–0.097 (0.915)	–0.442 (0.071)	–0.365 (0.074)	–0.032 (0.007)	0.009 (0.014)
Subjective prob. of accident	0.130 (0.142)		0.129 (0.140)	0.135 (0.144)	0.134 (0.143)	0.106 (0.473)	0.146 (0.485)	0.090 (0.056)	–0.073 (0.084)
N	966	927	1,130	934	966	927	1,130	934	

	Means (std. dev.)				OLS		Probit	
	Liability limit	Liability limit Has insurance	Has collision insurance Has liability insurance	Deductible <= \$500 Has collision insurance	Liability limit	Liability limit Has insurance	Has collision insurance Has liability insurance	Deductible <= \$500 Has collision insurance
R-squared	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pseudo R-squared					0.11	0.10	0.10	0.01

Notes: Liability limit regressions exclude individuals with indeterminate liability limits. Marginal effects and associated standard errors shown in cols. (7) and (8). The objective probability of an accident and the binary variable for any accident are not jointly significant in any of the regressions.

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

Table 5

Relationship between accident occurrence and insurance coverage

	Mean (std. dev.)	Any accident in last year (Wave 2)	
	(1)	(2)	(3)
<i>Dependent variable</i>			
Any accident in last year (Wave 2)	0.089 (0.285)		
<i>Insurance policy characteristics</i>			
Upper liability limit (\$100k)	2.939 (2.168)	0.004 (0.004)	0.004 (0.004)
Has collision insurance (0–1)	0.891 (0.312)	–0.004 (0.031)	0.003 (0.031)
<i>Accident probability, used</i>			
Objective probability of accident in last 3 years (Wave 1)	0.209 (0.099)		0.225 *** (0.085)
Any accident in last 3 years (Wave 1, 0–1)	0.212 (0.409)		0.075 *** (0.020)
N	962	962	962
Pseudo R-squared		0.00	0.05

Notes: Excludes individuals with indeterminate liability limits. The objective probability of an accident and the binary variable for any accident in the last 3 years are jointly significant in both regressions, $p < 0.001$.

*
 $p < 0.10$

**
 $p < 0.05$

 $p < 0.01$

Table 6**Moral Hazard**

Step		Speeding		Drinking and driving	
1:	Subj. prob. of reckless driving/ Penalty	-0.332	***	-0.089	***
2:	Obj. prob. of reckless driving/ Subj. prob. of reckless driving	1.000	\$	0.693	***
3:	Obj. prob. of accident/ Obj. prob. of reckless driving	0.046	**	0.048	***
	Obj. prob. of accident/ Penalty	-0.015		-0.003	
	Effect of moral hazard on accident rate between Waves 1 and 2 (mean=0.089)	-16.9%		-3.4%	

Notes: Marginal effects shown. Sources of marginal effects: Step 1-Table A2, row 6, col. 9 and row 7, col. 11; Step 2-Table A3, row 1, col. 1; Step 3-Table A3, row 2 and row 3, col. 3.

Penalty = 100% increase in premium

Excludes individuals without liability insurance

\$ Assumed value

p<0.10

**
p<0.05

p<0.01

Table 7

Private information and quality of insurer

Source:	Reader score		Overall score		Overall claims satisfaction		Overall purchase experience		Plan to renew	
	Consumer Reports	Insure.com	J.D. Power	Insure.com	J.D. Power	Insure.com	J.D. Power	Insure.com	J.D. Power	Insure.com
Panel A: Overall quality	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Objective probability of accident in last 3 years (Wave 1)	-1.814 (0.674)	***	-1.975 (1.229)		-0.319 (0.207)	**	-0.661 (0.315)		-5.857 (1.827)	***
Any accident in last 3 years (Wave 1)	0.021 (0.174)		0.096 (0.318)		-0.012 (0.054)		-0.048 (0.081)		0.288 (0.472)	
Risk preference	-0.117 (0.076)		0.136 (0.135)	0.151 (0.137)	-0.030 (0.023)		-0.037 (0.035)	0.141 (0.202)	0.184 (0.203)	
Subjective prob. of accident	0.505 (0.466)	0.676 (0.469)	0.209 (0.848)	0.358 (0.857)	0.100 (0.142)	0.135 (0.144)	0.114 (0.218)	0.191 (0.220)	-0.591 (1.267)	-0.150 (1.274)
N	792	792	786	786	801	801	819	819	786	786
R-squared	0.02	0.03	0.01	0.01	0.01	0.01	0.02	0.03	0.01	0.03
Significance level joint test ¹		0.006		0.117		0.100		0.021		0.002
Source:	Premium satisfaction		Claims service interaction		Local agent interaction		Accident forgiveness offered		Reason for buying: saw commercial	
	Consumer Reports	Insure.com	J.D. Power	Insure.com	J.D. Power	Insure.com	J.D. Power	Insure.com	J.D. Power	Insure.com
Panel B: Specific attributes	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Objective probability of accident in last 3 years (Wave 1)	-0.480 (0.191)	**	-0.598 (0.407)		-0.561 (0.382)	**	0.341 (0.159)		2.189 (1.254)	*
Any accident in last 3 years (Wave 1)	-0.003 (0.049)		-0.035 (0.105)		-0.046 (0.099)		0.025 (0.041)		0.445 (0.324)	
Risk preference factor	-0.041 (0.021)	* -0.036 (0.022)	-0.062 (0.045)	-0.040 (0.046)	-0.032 (0.042)	0.025 (0.018)	0.021 (0.018)	0.267 (0.139)	* 0.221 (0.139)	
Subjective prob. of accident	0.225 (0.132)	* 0.272 (0.133)	-0.119 (0.280)	-0.051 (0.283)	-0.164 (0.267)	0.130 (0.109)	0.090 (0.110)	-0.416 (0.867)	-0.745 (0.875)	

Source:	Premium satisfaction		Claims service interaction		Local agent interaction		Accident forgiveness offered		Reason for buying: saw commercial	
	<i>Consumer Reports</i>		<i>J.D. Power</i>		<i>J.D. Power</i>		<i>Insure.com</i>		<i>Insure.com</i>	
<i>Panel B: Specific attributes</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N	792	792	801	801	794	794	820	820	786	786
R-squared	0.02	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03
Significance level joint test [/]		0.009		0.110		0.103		0.019		0.031

Overall quality

Aggregate measure

Source:

Panel C: Aggregate quality

	(1)	(2)
Objective probability of accident in last 3 years (Wave 1)	-0.481 (0.231)	**
Any accident in last 3 years (Wave 1)	-0.017 (0.060)	
Risk preference	-0.037 (0.026)	-0.032 (0.026)
Subjective prob. of accident	0.015 (0.159)	0.066 (0.161)
N	828	828
R-squared	0.02	0.03
Significance level joint test [/]	0.027	

Notes

[/] Joint test is for combined effect of objective probability of accident and any accident, both in the three years before Wave 1.

Standard errors in parentheses

All specifications also include income, educational attainment, and race/ethnicity not shown.

* p<0.10

** p<0.05

*** p<0.01

Table 8

Premiums and quality of insurer

	Full sample	Premium			Low- or medium-risk/accident
		Low-risk/no accident	Medium-risk/no accident	High-risk	
	(1)	(2)	(3)	(4)	(5)
<i>Accident probability, used</i>					
Objective probability of accident in last 3 years (Wave 1)	682.895 ** (345.904)				
Any accident in last 3 years (Wave 1)	47.262 (80.775)				
<i>Insurance contract parameters</i>					
Upper liability limit (\$100k)	20.994 (15.549)	21.567 (27.953)	-7.371 (36.672)	51.866 ** (23.495)	20.098 (34.024)
Has collision insurance	431.843 *** (138.340)	348.713 (269.442)	611.180 ** (287.864)	428.229 ** (208.295)	441.939 (378.079)
<i>Insurer quality</i>	-102.236 ** (45.361)	-161.252 ** (81.903)	2.549 (105.805)	-104.468 (68.731)	-209.367 ** (95.038)
N	760	238	198	237	87

Notes: The dependent variable is the respondent's reported annual premium.

All specifications use a Heckman correction to account for selection into insurance, where the selection equation includes chargeable accidents, DWI arrests, cars in household, miles driven per week, drives to work, and risk preference, not shown. The premium equation also includes the number of adult (age $\geq$ 25) and young (age $<$ 25) drivers on the policy, the number of cars in the household, and the collision insurance deductible.

Standard errors in parentheses

* p<0.10

** p<0.05

*** p<0.01

Table 9

Private information by objective risk groups

	Means (std. dev.)				Any accident in last year (Wave 2)			
	Low-risk/no accident	Medium-risk/no accident	High-risk	Low- or medium-risk/accident	Low-risk/no accident	Medium-risk/no accident	High-risk	Low- or medium-risk/accident
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Any accident in last year (Wave 2)	0.049 (0.217)	0.071 (0.257)	0.119 (0.324)	0.152 (0.360)	***			
Objective probability of accident in last 3 years (Wave 1)	0.121 (0.030)	0.193 (0.020)	*** (0.096)	0.327 (0.039)	***			
Any accident in last 3 years (Wave 1)	0.000 (0.000)	0.000 (0.000)	0.318 (0.466)	*** (0.000)	1.000 (0.000)	***		
Net worth (\$100k)	4.021 (5.672)	3.011 (5.469)	** (6.916)	3.456 (4.436)	2.858 (5.436)	**	0.002 (0.002)	-0.001 (0.003)
Risk preference	-0.169 (0.834)	-0.005 (0.982)	** (1.076)	0.103 (1.118)	*** (1.118)	0.040 (0.013)	-0.016 (0.017)	0.023 (0.014)
Subjective prob. of accident	0.117 (0.130)	0.120 (0.137)	0.160 (0.156)	*** (0.153)	0.143 (0.153)	*	-0.077 (0.090)	*** (0.232)
N	344	310	387	125	337	305	381	119
Pseudo R-squared					0.10	0.06	0.04	0.02

Notes: Marginal effects and associated standard errors from probit in columns 5–8. Significance tests in cols. 2–4 are pairwise t-tests. The reference group is the low risk/no accident group.

*
p<0.10,
**
p<0.05,

p<0.01