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Are Drivers Who Use Cell Phones Inherently Less Safe?

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Abstract

Mobile phone usage while driving is increasing throughout the world. In this paper, we use survey data from 7,268 U.S. drivers to estimate the relationship between mobile phone use while driving and accidents. We hypothesize that drivers who use mobile phones while driving may be more likely to get into accidents than drivers who do not, even when they are not using the phone. We find evidence for the endogeneity of mobile phone and hands-free device usage, and our analysis suggests that individuals who are more likely to use hands-free devices are more careful drivers even without them. Once we correct for the endogeneity of usage, our models predict no statistically significant increase in accidents from mobile phone usage, whether hand-held or hands-free. Our results call into question previous cost-benefit analyses of bans on mobile phone usage while driving, which typically assume that such bans will have a salutary effect.

JEL Subject Codes: I18, R41, C35.

Keywords: cellular telephones and driving, safety regulation, selection effects.

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I) Introduction

Mobile phone use is nearly ubiquitous in the developed world. More than three-fourths of the U.S. population owns a mobile phone, and penetration exceeds 95% in Western Europe.[1] Many drivers want to use their phone while driving, although concern that such use increases accidents has prompted bans in many parts of the world. Much of Europe has banned the use of hand-held mobile phones while driving. In the U.S., California, Connecticut, New York, New Jersey, Washington state, Washington, D.C., and dozens of municipal governments have followed suit.

The goal of such bans is to reduce the number of accidents, but their impact is unclear. Although we are not aware of any case study showing that a ban in a particular area has reduced the vehicular accident rate, many studies purport to find a link between mobile phone use and crashes. However, no study to date has addressed the obvious question of whether phone use is endogenous. Is the driving of those who choose to use their phones while driving inherently less safe than that of drivers who choose not to? If it is, then the existing cost-benefit analyses of mobile phone use while driving (Redelmeier and Weinstein, 1999; Hahn, Tetlock, and Burnett, 2000; Cohen and Graham, 2003) may be suspect.

The statistical studies on mobile phone use and accidents (Redelmeier and Tibshirani, 1997; Violanti, 1998) on which the cost-benefit analyses are based estimate risk of use as a multiple of an individual's *unknown* baseline accident rate. While the statistical methods (conditional fixed-effects) used are robust to endogeneity of mobile phone usage, they cannot reveal whether such endogeneity exists. The cost-benefit analysis literature converts the risk multiples to a number of accidents potentially averted by a ban using average population accident rates in

[1] Subscriber data for the U.S. are from CTIA Wireless Quick Facts, December 2006 (http://www.ctia.org/content/index.cfm/AID/10323). Subscriber data for Europe is for 2006, from Market Intelligence Center, press release dated 31 January 2007 (http://mic.iii.org.tw/english/press/research_PR.asp?func=press&Doc_sqno=4641).

its calculations. If individuals who use mobile phones have different baseline accident rates than those who do not, however, using average rates to calculate the reduction in accidents from a ban would likely yield misleading results.

In a previous study (Hahn and Prieger, 2006b), we found that the impact of mobile phone use on accidents varies across the population. Samples of drivers who all had accidents are therefore composed disproportionately of individuals with large usage effects. As a result, previous estimates of the impact of mobile phone use on risk (Redelmeier and Tibshirani, 1997), based on accident-only samples, may therefore be overstated for the general driving population by about one-third.

In this paper, we explore whether mobile phone use is endogenous. The objective is to carefully analyze the relationship between mobile phone use while driving and accidents. We hypothesize that drivers who use mobile phones while driving may be more likely to get into accidents than drivers who do not, even when they are not using the phone. If so, mobile phone users are a selected group of riskier drivers, and valid statistical inference must be based on econometric models that correct for the endogeneity of use. We develop such models and apply them to data from a survey of more than 7,000 drivers that provides information on mobile phone use and vehicle accidents. The unique advantages of these survey data—more observations and more comprehensive than previous studies using data on individuals—are documented in Hahn and Prieger (2006b).

In our econometric models, we assume that collision risk is not only determined by mobile phone usage and other factors, but also by the driver's type. The term "type" refers to the unique, unobserved propensities of a driver to crash, and includes the influence of driving skill, temperament, and proclivity toward distraction on the road. The driver's type also affects the decision to use the phone while driving. The inherent type of the driver is not completely captured by any characteristics (such as age, sex, or income) that the econometrician observes, which raises the question of endogeneity and selection bias for any estimation sample.

To expand upon this idea, consider the stylized representation of determinants of accident risk in Figure 1. The determinants of collision risk begin with the type of driver on the left. Drivers' types range from very careless to extremely safe drivers. Figure 1 depicts the unobserved type affecting the amount of mobile phone usage while driving and whether the driver uses a hands-free device. Usage is also determined by external factors influencing demand for calling while driving, such as income and price of usage. The most natural story, which is supported by our analysis, is that more careless people are more likely to use the phone while driving, and less likely to use hands-free devices. Collision risk is determined by mobile phone usage while driving, external factors, and the driver's type. A simple observed correlation between mobile phone usage and collisions therefore confounds the direct causal effect from usage with the effect of the unobserved type. If riskier drivers are more likely to use mobile phones, then simple estimates of the impact on accident rates from mobile phone usage may be biased upward due to the common factor of the unobserved type influencing both usage and accidents.

The data support our hypothesis. Selection effects due to the endogeneity of mobile phone usage appear to be present. Our models find accident risk from mobile phone usage to be smaller in magnitude after correcting for endogeneity than before, and insignificant. Furthermore, correcting for endogeneity removes all significant effect of hands-free device usage on accidents, which calls into question bans on hand-held usage (which includes nearly all bans).

The plan of the paper is as follows. We review the literature on the effect of mobile phone use on driving in the following section. In section III, we describe our survey data. We report the results of our statistical work in section IV, and conclude in section V.

II) Literature Review

We provide a thorough review of the literature on the effects of mobile phone use on driving in Hahn and Prieger (2006b). In this section, we mention only the seminal study and then briefly update the review with recent work.

There are many studies now on mobile phone use and accidents. Some use individual or aggregate data on actual accidents, while others generate data from controlled experimental studies (often conductor in a simulator) or "naturalistic" studies (e.g., camera in the car) of drivers.[2] Hahn and Dudley (2002) and McCartt *et al.* (2006) review and critique this literature, and find that there is widespread agreement that using a mobile phone while driving increases the risk of an accident. The most influential study among policy makers is Redelmeier and Tibshirani (1997), who examine mobile phone records of Toronto drivers who had accidents to determine if the driver was using the phone at the time of the crash. By comparing the individual's behavior to a reference period at the same time the previous day, Redelmeier and Tibshirani (1997) estimate that a driver is 4.3 times as likely to have a collision while using a phone as when not using a phone. These results are widely quoted in the media and continue to be widely cited in policy discussions about banning phone usage while driving.

Hahn and Prieger (2006b) point out that there appears to be significant variation across individuals in the impact of identical amounts of phone use on accidents. Thus, Redelmeier and Tibshirani's (1997) methodology does not avoid selection bias, since their method uses only mobile phone users who had accidents, who are the ones with the highest expected impact from phone use. After correcting for this sample selection, Hahn and Prieger (2006b) find that Redelmeier and Tibshirani's (1997) accident multiplier may be overstated by about one-third and less precisely estimated than previously thought.

[2] See Hahn and Prieger (2006b) and Lissy *et al.* (2000) for citations.

Other recent studies include Strayer *et al.* (2006), who find in a simulator lab study that impairments associated with using a mobile phone while driving can be as strong as those associated with drunk driving. However, it is uncertain how impairments such as delayed braking time found in a traffic simulator translate to actual on-road accidents, especially since crash data analyses reveal that the number of crashes that may be attributed to mobile phone use is much smaller than experimental studies would predict (NHTSA, 1997). Commenting on the discrepancy, Esbjörnsson and Juhlin (2003) find that compensatory behavior by drivers in actual traffic situations may explain some of the difference.[3]

McEvoy *et al*. (2005) replicate Redelmeier and Tibshirani's (1997) methodology and findings with a sample of 456 Australian drivers. Their accident risk multiple of 4.1 from mobile phone usage is similar to that of Redelmeier and Tibshirani's (1997). In one of the few experimental studies using drivers in actual conditions, NHTSA (2005) observed ten participants in instrumented vehicles with two weeks driving each with no phone use, hand-held use, hands-free headset use, and hands-free use with voice dialing. The study finds no deterioration in measures of driving performance from any mode of usage. Finally, the largest naturalistic study to date (NHTSA, 2006) concluded from video observation of 241 U.S. drivers over 18 months that the collision risk multiple from dialing is 2.8 and from talking is 1.3 for hand-held mobile phones, although the latter is not statistically significant.

III) The Survey Data

We use the same survey data collected for Hahn and Prieger (2006b); see that source for an extensive description of the strengths and weaknesses of the data. Here we review the data's salient features. From retrospective survey responses on mobile phone usage and driving pat-

[3] Esbjörnsson and Juhlin (2003) demonstrate in an ethnographic study that drivers use a broad range of adaptive behaviors when using a phone while driving, to make the talk as safe as possible given the traffic situation.

terns, we create a panel data set with 26,572 quarterly observations (October 2001 to September 2002) on 7,268 individuals.[4]

Measurement of typical daily or weekly mobile phone usage while driving is categorical: no usage, 1-15 minutes per week, 2-20 minutes per day, 20-60 minutes per day, or more than one hour per day.[5] The other usage variable included in the estimations is whether the driver uses a hands-free device. Other variables collected in the survey include data such as annual mileage driven, duration and location (rural vs. urban and freeway vs. surface street) of typical commute, and demographic data for the drivers and their households. We discuss additional variables we use to control for other factors that can affect accident rates when we present our results.

Our survey respondents are not a random sample from the population (they chose to be recruited into an Internet survey panel). In Hahn and Prieger (2006b), we explore the composition of the sample. Summarizing that discussion, we note here that individuals in our sample are representative of the population in terms of age and regional distribution, but tend to be from areas with higher population and income. Due to an error by the survey administrator, two-thirds of the respondents in our sample are female.[6] We therefore explore single-gender samples in our estimations.

Our estimate of phone use while driving—73% use a mobile phone while driving at least occasionally (64% when adjusted with survey weights)—is on the high end of the range found in other surveys (see Table 1) from the time. Thus, underreporting of usage does not appear to be a problem. We also find that (after weighting) 28% of drivers and 44% of those who use a mobile

[4] There is an average of 3.7 quarters per individual, because a quarter is missing if the individual did not drive a 1999 or newer model year vehicle that quarter. We removed quarters with older vehicles to homogenize the safety features (in particular, the presence of front air bags) among vehicles.

[5] Typical usage is asked for 2001 and 2002, but the usage variable can also vary quarter to quarter due to when the driver used a mobile phone, which is known by quarter.

[6] Due to an error by the survey administrator, the survey offer was sent to a panel that was balanced with respect to general Internet users' age, Census division, household income and size, and market size, but not on gender.

phone while driving use a hands-free device of some sort at least sometimes with their phone while driving.

The accident rates in the sample are shown in Figure 2.[7] The overall accident rates in our sample (5.4% of drivers per year; 6.3% of drivers per year using survey weights) are comparable to those of the general driving public in the U.S. (NHTSA, 2004). Those who use the phone while driving have the highest accident rate (5.9% raw, 7.1% weighted). Those who have a mobile phone but claim they do not use it while driving have a lower accident rate (3.7% in the raw data) than those who do not have a mobile phone (4.4%).[8] The latter may indicate the presence of selection effects, if those who could use a phone while driving but choose not to do so are safer drivers. However, the weighted averages do not differ between these two groups, and the accident rates do not control for annual mileage or the other factors, so no conclusion can yet be drawn. Figure 2 also shows that drivers who use the phone more or use hands-free devices less while driving have higher accident rates (except for the highest category of phone use). In the following section we turn to estimations that control for selection effects and other factors.

IV) Estimations

Our estimations are from econometric models for panel data on accidents. The dependent variable is the number of collisions in a quarter for a driver. The explanatory variables of interest are binary indicator variables for average mobile phone usage minutes while driving (none, 1-15 minutes per week, 2-20 minutes per day, 20-60 minutes per day, or more than one hour per day) and usage of a hands-free device while driving (never, sometimes, all the time). As in much of the traffic safety literature, we assume that explanatory variables have a multiplicative effect on the mean accident rate. We present results from simple Poisson models, instrumental variables estimations, and multiple-equation models. The latter two allow us to explore the endogeneity of mobile phone and hands-free usage.

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[7] See also Table 1 of Hahn and Prieger (2006b) for additional summary statistics of the data.
[8] An equality-of-proportions test for these three categories of users has a two-sided *p*-value of 0.012.

A) Poisson Estimations

Our first estimation is Poisson regression performed on the pooled data (all quarters and all drivers).[9] In Poisson regression, accidents are modeled as a count variable. While the Poisson model does not include fixed or random effects for panel data, if they are present then Poisson regression yields consistent but inefficient estimates.[10] We calculate standard errors robust to the presence of heteroskedasticity and correlation of any kind among an individual's observations. Although the Poisson estimates are inconsistent if mobile phone usage or vehicle choice are endogenous, for which we find evidence in the following sections, the estimations in this section reveal correlations in the data and provide a baseline useful for comparing with more general models that correct for endogeneity.

The estimation results are presented in Table 2. Coefficients in a Poisson model are easiest to interpret when exponentiated, which yields the "incident rate ratio" (IRR) for the variable. For example, if the driver is female, she has $\exp(\beta_{Female})$ times as many expected accidents as does a male driver. Thus, variables that are correlated with higher accident rates have IRR's greater than one.

The mobile phone usage coefficients represent the incremental risk over not having a mobile phone. If mobile phone usage is not correlated with accident rates, the IRR's for all the usage categories would be 1.0.[11] In Estimation 1, which controls only for gender, more phone usage while driving is associated with higher accident risk for women in our sample. Redelmeier and Tibshirani (1997) also find that mobile phone usage by women appears to be riskier than us-

[9] The estimations in this subsection differ from those in section V.B of Hahn and Prieger (2006b) only through inclusion of log car weight as an explanatory variable, and our discussion here draws heavily upon our earlier work. We include car weight to ensure comparability of Estimations 1 and 2 with the later estimations.

[10] Consistency in the presence of individual effects, however, requires the effects to be mean independent of the regressors. See section 3.2.3 of Cameron and Trivedi (1998).

[11] These risk multipliers cannot be compared directly to Redelmeier and Tibshirani's (1997) risk multiple of 4.3 or McEvoy *et al*.'s (2005) multiple of 4.1. Our risk multipliers are for the number of accidents in a year given an average level of phone usage, whereas the other studies' risk multipliers imply that the *instantaneous* accident risk for the individual is 4.1-4.3 times as high when using a mobile phone as when not.

age by men.[12] The men's effects are not statistically significant at the 5% level, while for the women all categories but that for the lowest usage have significant effects. The increase in accident risk for women rises with the amount of usage. Also, use of hands-free devices is correlated with lower accident risk, at least for women. The IRR for women who always use a hands-free device is around 0.5, implying a halving of accident risk. The average IRR among mobile phone users is 1.30.[13]

Factors other than phone usage may influence accident risk. We include covariates such as demographics, weather, and driving variables in Estimation 2.[14] The estimated effects of mobile phone and hands-free usage on accidents for women remain significant, although they are smaller. The lower average IRR for mobile phone users in Estimation 2, 1.05, indicates that some of the correlation between usage and accidents found in Estimation 1 is due to omitted variables such as miles driven and vehicle choice. Some of the covariates have significant effects. Married drivers have lower accident risk. Younger and older drivers crash more, with the minimum accident risk occurring around age 53. Full time employment and longer personal commuting time are correlated with increased accident risk. More daylight hours are correlated with decreased accident risk. Car weight has been found in external data sets to be highly correlated with (and thus to control for) other vehicle safety variables such as antilock brakes and four-wheel drive,[15] and heavier cars are associated with fewer accidents in our sample. The coefficient of -0.63 (IRR = 0.53) for log car weight is the elasticity of expected accidents with respect to log car weight. Other variables have expected but insignificant effects: men have more accidents than women. Higher annual mileage, local population density, and average local commut-

[12] Few studies have examined gender differences in the effect of mobile phone usage. Briem and Hedman (1995) find that men control their vehicles slightly better when using mobile phones on slippery roads than do women in a simulator study. Laberge-Nadeau *et al*. report higher risk multiples for several types of accidents for women than men, but do not address the statistical significance of the difference. McEvoy *et al*. (2005) do not find phone usage by women to be riskier than usage by men..

[13] The average risk multiplier reported is calculated conditional on mobile phone usage and weighted by the fraction of drivers in each phone and hands-free device usage category.

[14] The weather data are from National Climatic Data Center, Database TD3220, and are matched to the household's ZIP code. Hours of daylight are calculated from the latitude of the ZIP code.

[15] See, *e.g.*, Kahane (2003), pp. 65 and 126. The vehicle weights are from the *Automotive News Market Data Book*, various years.

ing time are all correlated with higher accident risk. In Hahn and Prieger (2006b), we estimated many other models with alternative sets of explanatory variables and different samples of the data or weighting schemes, with generally similar results.

If there is a causal link between hand-held phone usage and accidents, bans restricting hands-held usage while driving may be justified. However, Estimations 1 and 2 are valid only if hands-free usage is exogenous, a suspect assumption we explore and reject in the following two subsections; therefore, the results here have no significance for policy.

B) An IV Model for Endogeneity

We turn now to our hypothesis that the use of mobile phones and hands-free devices while driving is endogenous, and show that after controlling for endogeneity, mobile phones do not appear to increase accidents and hands-free devices do not appear to reduce accidents. The endogeneity is due to the unobserved type of the driver, which incorporates attitudes toward risk and the individual's degree of carelessness. The unobserved type is taken to be constant over our relatively short time span and fully captured by an individual-specific effect. We now present the notation to clarify our models as we go beyond the basic Poisson model.

Let $i = 1, \ldots, N$ index individuals and $t = 1, \ldots, T$ index quarters. Denote the number of accidents in period t for individual i as y_{1it}, the amount of mobile phone usage as y_{2it}, and log car weight (a safety characteristic) of the individual's primary vehicle as y_{3it}. Conditional on covariates $(x_{it}, y_{2it}, y_{3it})$ and an individual-specific effect v_i, the number of accidents is assumed to follow the Poisson distribution with mean

$$E(y_{1it}|x_{it}, y_{2it}, y_{3it}, v_i) = s \exp(\beta' x_{1it} + \gamma' y_{2it} + \delta' y_{3it}) v_i \tag{1}$$

where s is 0.25, the period length in years, x_{it} is a vector of exogenous variables, and v_i is an unobserved individual-specific multiplicative effect.[16] The multiplicative formulation treats the

[16] It is common in vehicle accident studies to perform all analysis on the accident rate per vehicle mile traveled (VMT). In terms of equation (1), this would mean replacing time with VMT as our measure of risk exposure. Using VMT as the exposure measure is equivalent to including log VMT as an explanatory variable in equation (1) and restricting the coefficient to one. Given that individuals may not be able to accurately report their VMT, we instead

unobservable v_i symmetrically with observables y_2 and y_3. The coefficient on the mobile phone usage variable, γ, is of primary interest. The mixing term v_i induces heterogeneity into the mean accident rate among individuals who are observably similar. We assume v_i may be correlated with y_2 and y_3; in other words, mobile phone usage and vehicle safety may be endogenous.

The instruments we use for phone usage are inspired by Hausman and Taylor's (1981) estimator for linear models in which endogeneity is due to correlation of a time-varying regressor, here mobile phone usage, with the individual-specific effect v_i but not the idiosyncratic error peculiar to an individual in a single time period. In such cases, instruments come from "inside" the equation: the deviations from an individual's mean of the endogenous regressor over time (*e.g.*, $y_{2it} - \bar{y}_{2i}$) will be uncorrelated with the individual-specific error. We also treat vehicle safety choice, as reflected by vehicle weight, as endogenous. We use weight because there is evidence that heavier cars are safer for their occupants in a crash than are lighter cars, so that car weight may embody endogenous safety choices.[17] We instrument for car weight with local gasoline prices and weather variables.

Linear IV methods for additive means and errors are not appropriate for the multiplicative mean and error of accident equation (1). We instead define appropriate moment conditions for (1) and use the nonlinear instrumental variables (NLIV) estimator (Amemiya, 1974). To recast the Poisson model in the NLIV framework, note that (1) implicitly defines a multiplicative model

$$y_{1it} = s \exp(\beta' x_{it} + \gamma' y_{2it} + \delta y_{3it})\, \xi_{it} \qquad (2)$$

include it (measured for the quarter as reported annual VMT divided by four) as an explanatory variable but leave its coefficient unrestricted.

[17] A recent federal study concludes that the heavier the vehicle, the lower the risk of a fatality to any occupant in a crash, for all but the heaviest vehicles (Kahane, 2003). These results were widely reported in the press. Summarizing other studies on vehicle weight and crash safety, the Los Angeles Times (February 18, 2003, part 3, p.1) concluded that despite conflicting evidence on heavy vehicles and *overall* fatalities, "[n]o expert contends that, all other things being equal, heavier vehicles aren't safer for their passengers than are light ones." The association between vehicle weight and crash safety has been known for decades; Crandall and Graham (1989) cite many such studies, dating back to 1977. Recent studies indicate that heavier vehicles may crash more, negating their greater safety given a crash (Gayer, 2004). However, for vehicle weight to be a good proxy for vehicle safety choice, it is only required that car buyers *believe* that heavier cars are safer.

where $\xi_{it} = v_i e_{it}$, e_{it} is a multiplicative error satisfying $E(e_{it}|x_{it}, y_{2it}, y_{3it}, v_i) = 1$ by definition, and other notation follows (1) (Windmeijer and Santos Silva, 1997). The endogeneity of y_2 (binary indicator variables for the mobile phone and hands-free device usage categories) and y_3 (log car weight) implies that $E(\xi_{it}|x_{it}, y_{2it}, y_{3it}) \neq 1$, which precludes Poisson estimation from yielding consistent estimates. As discussed above, we restrict the correlation between y_2 and ξ_{it} to come only through v_i, the individual-specific error. We place no such restriction on y_3. If instruments z_{it} can be found such that $E(\xi_{it}|z_{it}) = 1$, then $E(\xi_{it} - 1|z_{it}) = 0$ and solving for ξ_{it} from (2) leads to the conditional moment condition

$$E\left(\frac{y_{1it}}{s\exp\left(\beta' x_{it} + \gamma' y_{2it} + \delta y_{3it}\right)} - 1 \middle| z_{it} \right) = 0 . \tag{3}$$

The NLIV procedure minimizes the objective function $(\boldsymbol{\xi} - 1)'\mathbf{Z}'(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}(\boldsymbol{\xi} - 1)$, in the usual matrix notation, where $\boldsymbol{\xi}$ is replaced with functions of the data as in (3). Following our treatment in the previous section, we pool the data and adjust standard errors for clustering on individuals. The NLIV estimator is consistent as long as (3) holds, even if accidents do not follow a Poisson stochastic process, there is additional individual and period-specific heterogeneity, or y_2 and y_3 are endogenous.

The mobile phone usage categories for y_2 are collapsed from those used in the Poisson estimations into two categories: 1-15 minutes per week and higher amounts of usage. Grouping the higher-usage categories increases the precision of the instrumental variables estimations, because convergence was difficult to obtain with more finely cut categories. We treat the decision to own a mobile phone as exogenous.

Following Hausman and Taylor (1981), the instruments include all exogenous variables and the deviations from an individual's mean over time of all time-varying variables (except car weight), including y_2.[18] The deviation from average mobile phone use while driving for an indi-

[18] Following Windmeijer and Santos Silva (1997), the predicted values of the binary endogenous variables from first stage probit regressions are also included as instruments.

vidual, $y_{2it} - \bar{y}_{2i}$, is a valid instrument for y_{2it} under the maintained assumptions (which we test). However, this instrument performs poorly for the men, because the "within" standard deviation for mobile phone usage for men is only about two-thirds what it is for the women. This led to difficulty obtaining convergence of the estimator for the combined sample. Therefore, we estimate the NLIV model only for the women. Given that Estimations 1 and 2 suggested that impacts of mobile phone use on accidents are not significant for the men, we do not view this as a drawback.

For car weight, the additional instruments are local gasoline price in levels and squares and two weather variables: the number of days with snowfall and total snowfall depth in a quarter.[19] The gas price is for the MSA, where available, or for the state.[20] After controlling for miles traveled, the price of gas should not affect the accident rate. Households in areas with more snowfall may be more likely to purchase heavier vehicles such as SUVs and other vehicles with four-wheel drive and traction control, both of which add to vehicle weight. As with the weather variables included in x, snowfall is measured at the weather station closest to the driver's household. To ensure the snowfall instruments are properly excluded from the accident equation (2), we follow Gayer (2004), who also uses snow-related variables as instruments, and use snow measurements at a time other than the current period t. Here, we use measurements for the same season of the non-current year of our sample (i.e., for quarters in 2002 we use snowfall from 2001, and vice versa). Given that we already control for current weather in the accident equation, out-of-period snowfall measurements should not violate equation (3).[21]

Table 3 contains the estimation results for the NLIV model, as well as for the analogous Poisson model with the collapsed phone usage categories. The mobile phone and hands-free coefficients (here, for women) are of greatest interest, given the results of the Poisson estimations.

[19] Gas prices include state taxes and are from *Petroleum Marketing Monthly*, Energy Information Administration, Department of Energy, and *Historical Trends in Motor Gasoline Taxes, 1918-2002*, American Petroleum Institute.
[20] A metropolitan statistical area (MSA) is an area defined by the U.S. Census Bureau that includes an urban core and the surrounding areas having a high degree of social and economic integration with the core.
[21] If the two other-year snow variables are included in Estimation 2, they are not statistically significant, evidence corroborating (but not proving) that they satisfy the exclusion restriction.

Estimation 3 shows a pattern similar to the previous Poisson estimations: women who use the phone more than 15 minutes per week while driving have significantly more accidents (IRR = 1.65), and women who use a hands-free device all the time have significantly fewer accidents (IRR = 0.52). Once the endogeneity of usage is controlled for in the IV estimation, the picture changes markedly. There is evidence that mobile phone usage and car weight are indeed endogenous: Hausman tests soundly reject the null hypothesis of exogeneity at any reasonable significance level (see bottom of Table 3).[22] Importantly, the magnitude of the mobile phone usage coefficients drops in the IV estimation. The IRR for women who use the phone more than 15 minutes per week while driving falls from 1.65 to 1.19. Furthermore, neither of the mobile phone usage coefficients is significant once we control for endogeneity.

Regarding hands-free device usage, the IRR for the "always use" category rises to 0.73 and neither coefficient is significant. Many other field and laboratory studies have also found that use of hands-free devices does not reduce accident risk (e.g., Redelmeier and Tibshirani, 1997; Haigney and Taylor, 1999; Crawford *et al.*, 2001; Strayer and Johnston, 2001; and Strayer *et al*., 2003; McEvoy *et al*., 2005). Together, the results for mobile phone and hands-free device usage indicate that a large part of the apparent connection for women between usage and accidents (if not all) in the Poisson estimations is due to endogeneity. Of less importance for our main investigation in this paper, but interesting in its own right, is that the impact of car weight switches to increasing accidents in the IV estimation. This finding is in accord with a recent study indicating that heavier vehicles crash more than lighter vehicles after controlling for endogenous vehicle choice (Gayer, 2004).

IV estimation can lead to misleading inference if the instruments are invalid or weak. In particular, the deviations from average mobile phone usage are invalid instruments if the driver's type changes quarter to quarter. Note that modeling the endogeneity of mobile phone usage only through the individual-specific type v_i does not mean that a driver may not experience transitory

[22] The Hausman tests were conducted in comparison to pooled Poisson MLE (Estimation 3). Alternative Hausman tests, comparing the NLIV estimates to estimates from a random effects Poisson MLE, also convincingly reject the exogeneity of the mobile phone, hands-free device, and vehicle weight variables.

recklessness that increases both the propensity to use a mobile phone and to have an accident. Rather, it requires that the possibility of such behavior *on average during a quarter* does not change period to period. We test the validity of the instruments with many tests of the overidentifying restrictions in the models (see bottom of Table 3). None of these tests reject the null hypothesis that the instruments are valid at conventional significance levels.[23]

Although formal tests for weak instruments are available for linear IV, these do not apply to our model with multiplicative mean and errors.[24] As noted in Cameron and Trivedi (2005), however, formal tests are unnecessary to some extent because weak instruments are easily detected if standard errors are much larger when IV is used. The standard errors of the IV estimates are generally about twice the size (or less) of the corresponding Poisson standard errors, which is better than the performance of IV in many published studies.[25] Even if the standard errors in the IV estimation were as small as are those in Estimation 3, the coefficients for mobile phone and hands-free device usage would still be statistically insignificant.

C) A Multiple-Equation Model for Heterogeneity and Endogeneity

The IV model suggests that mobile phone and hands-free device usage is endogenous in the accident equation, but does not directly reveal the sign of the correlation between the unobserved determinants of accidents and phone usage. In addition, the IV estimates rely on instruments for mobile phone usage from within the accident equation, which is not a commonly used

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[23] We report four overidentification tests in Table 3: an F statistic assuming homoskedastic errors, and three tests robust to clustering on individuals: Hansen's J statistic, a C statistic to test the mobile phone usage and hands-free "deviations from individual mean" instruments, and another C statistic to test the gasoline price and weather instruments for car weight (see Hayashi (2000) for details of these tests).

[24] Informally applying tests for linear IV may give some idea of the strength of the instruments, however. We examined F statistics for the hypothesis that the coefficients on the identifying instruments are zero in first stage OLS regressions. The literature on weak instruments suggests that F statistics below the range of five to ten may lead to non-negligible finite sample bias in the second stage linear IV estimation (Staiger and Stock, 1997). The F statistics for the endogenous variables are all above 70, with the exception of car weight (F = 5.0, p-value = 6.2E-13). These F tests are meant to be suggestive only.

[25] For example, in Levine and Zimmerman (2005), IV standard errors are about five times their OLS counterparts. In Cohen and Dehejia (2004), the same multiple is four. In neither case are weak instruments discussed. These studies were selected by finding the most recent articles (at the time of the search) in *The Journal of Public Economics* and *The Journal of Law and Economics*, respectively, that used IV estimation. Cameron and Trivedi (2005) use a multiple of 10 as an example of weak instruments.

method. In this section, seek to corroborate our findings by explicitly modeling the endogeneity of the use of mobile phones and hands-free devices while driving in a parametric multiple-equation system. Our approach here allows us to estimate explicitly the nature of the endogeneity, while relying on parametric identification and the more traditional source of instruments, namely variables that do not enter the accident equation.

Our three equation model adds equations for mobile phone usage and car weight to the Poisson accident equation (1), to allow usage and car choice to be endogenous:

$$y^*_{2it} = \beta_2' x_{2it} + u_{2it} \tag{4}$$

$$y_{3it} = \beta_3' x_{3it} + u_{3it} \tag{5}$$

Equation (1) again is the equation for the quarterly accident counts. Equation (4) is for mobile phone usage. We explore two definitions of y_2 in this section: minutes of use while driving and usage of a hands-free device. Because usage levels are categorical, we impose the ordered probit observation rule: instead of observing the latent, normally-distributed y^*_2 in (4), we observe y_2, which takes one of K discrete values. Each value of y_2 represents a different class of mobile phone usage while driving. In one set of estimations, the classes are the five minutes–of-usage categories for phone owners; thus $K = 5$. With this definition, equation (4) is present only for those individuals who have a mobile phone. In the other set of estimations, the mobile phone usage classes for y_2 are the amount of hands-free device usage while driving: never, sometimes, and all the time. Here K = 3, and (4) is present only for those individuals who both have a mobile phone and use it while driving.[26] For $k = 0,1,\ldots,K\text{-}1$, the observation rule is

$$y_{2it} = k \text{ if } \kappa_k < y^*_{2it} \le \kappa_{k+1} \tag{6}$$

[26] In other words, we assume that there is no selection bias caused by the choice to have a phone or not, and that selectivity problems arise with choice of hands-free usage only when the individual already uses a phone while driving.

By convention, $\kappa_0 = -\infty$, $\kappa_1 = 0$, and $\kappa_K = \infty$. The third equation, (5), is for log car weight, where y_3 is a fully observed normal random variable.

The errors in equations (1), (4), and (5) are specified as:

$$v_i = \exp(\alpha_{1i}) \tag{7}$$

$$u_{2it} = \alpha_{2i} + \varepsilon_{2it} \tag{8}$$

$$u_{3it} = \alpha_{3i} + \varepsilon_{3it} \tag{9}$$

where the α are correlated across equations but the ε are not. The random effects u_{it} are composed of individual-specific components α_i and idiosyncratic shocks ε_{it}.[27] The vector $(\varepsilon_{2it}, \varepsilon_{3it})$ is normally distributed with zero mean and covariance matrix

$$\Sigma_\varepsilon = \begin{bmatrix} 1 & 0 \\ 0 & \tau^2 \end{bmatrix}$$

and $E(\varepsilon_{kit}\varepsilon_{ljs}) = 0$ if $k \neq l$, $i \neq j$, or $t \neq s$.[28] The individual-specific random effect $\alpha_i = (\alpha_{1i}, \alpha_{2i}, \alpha_{3i})$ is normally distributed with mean $(-\sigma_1^2/2, 0, 0)$ and covariance matrix

$$\Sigma_\alpha = \begin{bmatrix} \sigma_1^2 & \rho_{12}\sigma_1\sigma_2 & \rho_{13}\sigma_1\sigma_3 \\ \rho_{12}\sigma_1\sigma_2 & \sigma_2^2 & \rho_{23}\sigma_2\sigma_3 \\ \rho_{13}\sigma_1\sigma_3 & \rho_{23}\sigma_2\sigma_3 & \sigma_3^2 \end{bmatrix}$$

and is assumed to be independent of x.[29] The α are independent of ε for all individuals and periods, and $E(\alpha_i\alpha_j) = 0$ if $i \neq j$. With this specification, y_2 is endogenous in (1) if $\rho_{12} \neq 0$ and y_3 is endogenous if $\rho_{13} \neq 0$. In addition to the coefficients of interest $(\beta_1, \gamma, \delta)$, the model requires estimation of nuisance parameters $(\beta_2, \beta_3, \sigma_1^2, \sigma_2^2, \sigma_3^2, \rho_{12}, \rho_{13}, \rho_{23}, \tau, \kappa)$.[30] We estimate the mod-

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[27] Because there is no evidence of heterogeneity in the mean accident rates after controlling for α_{1i} and covariates, we do not include an additional random effect ε_{1it} in (7). See Hahn and Prieger (2006a), Appendix B.10, for details of the formal tests. If ε_{1it} is added to the model, the estimate of its variance is nearly zero.

[28] The variance of ε_2 is fixed for identification in the ordered probit equation.

[29] The mean of α_1 is non-zero so that $E[\exp(\alpha_{1i})|x_{1it}, y_{2it}, y_{3it}] = 1$.

[30] When y_2 takes the definition of hands-free device usage, there is one minor modification to the above. In this case y_2 does not vary over time for an individual, so ε_2 is subsumed into α_2 and is dropped from the model.

el by MLE. Given the parametric assumptions, it is possible to find a closed-form expression for the density of all quarters of an individual's observations on $(y_{1it},y_{2it},y_{3it})$ conditional on v_i, denoted $f_i(y_i|v_i)$. The likelihood for MLE is then

$$\ln L = \sum_{i=1}^{N} \log \int_0^\infty f_i(y_i \mid v_i) dF(v) \qquad (11)$$

where $F(v)$ is the lognormal density of v. The integral is evaluated numerically and MLE proceeds as usual; see the appendix for the likelihood function and details.[31] We have not found this random effects panel Poisson-ordered probit-normal model developed elsewhere in the literature, but we use standard techniques to solve for the likelihood of multiple equation models for mixed continuous and discrete variables.

The covariates for the accident equation (1) are similar to those of Estimations 2-4. We use two sets of covariates for x_2 in (4), the mobile phone usage equation. The "small set" contains several variables also included in x_1 (age, mileage, commute length, drive mostly on freeways, employment status, gender, and marital status), and some that are not. These latter "instruments" are variables that potentially affect prices, quality, and competition in the mobile phone service market.[32] When competition is stronger, mobile phone service providers may offer lower prices, higher service quality, and may be more likely to offer hands-free devices with subscription, all of which may be correlated with minutes of use and hands-free device usage. Our mobile phone market variables are the cellular antenna site density within 25 miles of the

[31] This estimation problem is also a candidate for simulated maximum likelihood. However, given that expectation need be taken over a univariate random variable only, numerical integration of the likelihood via Gauss-Hermite quadrature is tractable and yields more precise estimates than simulation.

[32] Unlike linear systems of equations, there are no exclusion restrictions for x_1; the Poisson parametric assumption alone identifies the coefficients in (1). Thus, x_2 and x_3 need not contain variables not found in x_1, even when y_2 and y_3 are endogenous in (1). Due to the tenuous nature of identification solely through functional form, we do not rely on this to identify the system but instead use the instruments discussed here.

household,[33] and two industry cost shifters: the average wage in the cellular industry, and the average electricity price in the state.[34] The small set also includes whether the household has cable TV service, a variable related to willingness to adopt modern communications technology.

The second, larger set of covariates for x_2 includes the small set plus additional demographic variables that may influence phone and hands-free device usage: race and ethnicity indicators, household size, income, and whether the driver got married in the last two years. None of these variables appear in x_1, but their exclusion may be harder to defend than for the excluded variables in the small set. For x_3 in the car weight equation (4), we use age and age squared, marital status, commute length, and two variables not included in x_1: gas price in levels and squares. In addition to this small set of covariates, we also use a larger set of covariates for x_3.[35] All equations include region and quarter fixed effects.

To test for the endogeneity of mobile phone use and car weight in the accident equation, we first define y_2 to be mobile phone usage minutes while driving. Based on estimations for various samples (men and women separately and together) and using both the small and large sets of instruments, we cannot reject the hypothesis that there is no endogeneity in the accident equation. The endogeneity parameters ρ_{12} and ρ_{13} are statistically insignificant. This is in contrast to IV estimations above, in which there is evidence that usage is endogenous, and the failure to reject exogeneity here may indicate that our statistical tests have low power in this model. The estimated mobile phone effects differ little from the corresponding Poisson estimations and we do not report the results here.

[33] This variable was constructed by taking the number of cellular antenna sites within 25 miles of the household's location (as proxied by their five digit ZIP code centroid), and dividing by the population of all Census tracts that overlap with that circle. The antenna data are from the FCC's cellular tower registration database.
[34] The county average wage is used when available, and the state average is used when not. Data are from the U.S. Bureau of Labor Statistics. The electricity price data are from the Energy Information Administration, U.S. Department of Energy.
[35] The variables new to the large set are racial and ethnicity indicators, income, home ownership, additional employment status indicators, and the household size. They are significant in OLS estimations with log car weight as the dependent variable.

However, when we switch the role of the second equation and let it represent usage of a hands-free device, we confirm that usage is endogenous. In this model, only usage of hands-free devices is treated as endogenous in the accident equation. Use of a hands-free device may be endogenous if, for example, drivers that are inherently more careless are also less likely to use a headset while speaking on the phone. Estimation results are presented in Table 4.[36]

Of most interest from the estimations are the following results. The correlation between the accident equation and the hands-free equation, ρ_{12}, is large and negative in every specification we tried, regardless of the instrument set or sample used. A finding of negative correlation between α_1 and α_2 implies that unobserved factors that make an individual more likely to use a hands-free device also make the individual a safer driver, independent of any causal effect of mobile phone usage mode. Stated less technically, drivers who choose not to use a hands-free device are worse drivers to begin with. Results regarding the statistical significance of the negative correlation vary across specifications, but the preponderance of the evidence leads us to reject the hypothesis that use of hands-free devices is exogenous.[37]

There is no evidence of significant reductions in accidents from the use of hands-free devices, as opposed to the large effects found in Estimations 1 and 2, in which ρ_{12} is constrained to be zero. This corroborates our similar finding in the IV estimation. In fact, the IRR's for the hands-free variables are all greater than one. None of these IRR's is statistically significant, but it may be that some aspects of hands-free device usage lead to greater driver inattention.[38]

[36] Coefficients for the mobile phone and car weight equations are not reported in Table 4, but generally had plausible signs. See Table B.13.5 in Appendix B.13 of Hahn and Prieger (2006a).

[37] For the male sample, *t* tests of $\rho_{12} = 0$ have *p*-values below 0.001. The LR statistics testing the full models vs. their restricted counterpart lacking heterogeneity and correlation (see the appendix for details) also have *p*-values less than 0.001. For the female sample, the *t* tests do not have small *p*-values but the LR statistics do. In combined gender estimations (results reported in Hahn and Prieger (2006a)), *t* tests of $\rho_{12} = 0$ have low *p*-values (below 0.01) when the large set of instruments is used but not the small set. For both instrument sets, the LR statistics have *p*-values less than 0.001.

[38] For example, a consumer review of several hands-free devices found that fumbling with putting on a headset when answering a call and the poor audio quality of some hands-free phones may be more distracting than using a handset (Susan Stellin, "Hands-Free Calling Options for the Road," *New York Times*, July 26, 2001, p.G9).

We also find that when hands-free usage is treated as endogenous, the effects of minutes of mobile phone usage while driving are smaller for the women than in the simple Poisson models. In Estimations 6 and 8, the IRR's for minutes of usage are lower for each variable than in Estimations 1 and 2. Finally, the correlation between the accident equation and the vehicle safety equation is generally estimated to be positive, implying that drivers choosing heavier cars have a higher baseline accident rate to begin with.

We also explored IV estimations as in the previous section, but using the instruments from this section instead of the deviations from an individual's mean over time of the time-varying variables. This avoids the parametric assumptions of our three-equation model. The results, reported in Hahn and Prieger (2006a), lead to similar conclusions as Estimations 4-8. Exogeneity tests confirm that usage is endogenous. When the usage and vehicle weight variables are treated as endogenous, all significance of the impacts of the mobile phone minutes of usage variables goes away (whether using the small set or the large set of instruments). Also, the magnitude of the female mobile phone effects fall to modest levels, and the large reduction in accidents due to the use of hands-free devices by women implied in Estimations 1 and 2 disappears. These IV results confirm the findings from the multiple-equation models that selection is present and that correcting for endogeneity removes all certainty about the impact of usage on accidents (in the sense of statistical significance).

V) Conclusion

Our approach for estimating the relationship between mobile phone use while driving and accidents is the first to test for the endogeneity of mobile phone and hands-free device usage. We find evidence of selection effects. Our analysis suggests that individuals who are more likely to use hands-free devices drive more carefully even without them. Once we correct for the endogeneity of usage, our models predict no statistically significant increase in accidents from mobile phone usage, whether hand-held or hands-free. The results here join our earlier work (Hahn and Prieger, 2006b) in calling into question previous cost-benefit analyses of bans on mobile phone usage while driving. Unlike our approach in Hahn and Prieger (2006b), the models here do not explicitly include random coefficients for usage. However, if they are present, then our IV estimates of the mobile phone effect are still consistent for the average effect under plausible assumptions (see the appendix).

Because we find there is more uncertainty than previously suggested in the relationship between mobile phone use while driving and accidents, cost-benefit analyses of different types of proposed bans should reflect this uncertainty. In addition, policy makers should treat the results of cost-benefit analyses with care.

Ironically, many policy makers treat the link between mobile phones and accidents as well established. For example, in a statement on legislation restricting mobile phone usage while driving in California, a state legislator (apparently referring to Redelmeier and Tibshirani (1997)) avowed, "Study after study has shown that people who use cell phones while they're driving are four times as likely to get into an accident."[39] Another legislator pronounced that "the difference between hands-free and hand-held is life and death."[40] Yet, there is little scientific evidence to suggest that hands-free usage is actually safer while driving, and our results suggest that it is not.

In reality, the case for regulation may be less clear now than it was five years ago. However, our results do not imply that no restrictions should be placed on drivers using mobile phones. Instead, we provide additional considerations and evidence that policy makers should consider before regulating.

[39] California state senator Debra Bowen, speaking in support of SB 1582, quoted in *The San Diego Union-Tribune*, May 29, 2004, p. B-8.
[40] Statement of May 26, 2006 from the office of state Senator Joe Simitian, speaking in support of the recently enacted ban on hand-held usage in California.

Appendix

This appendix contains additional information on the data and estimations. Other supplementary material, including the survey instrument, can be found in Hahn and Prieger (2006a).

A.1 Likelihood of the Multiple Equation System

Here we present the likelihood for the model defined in equations (1) and (4)-(9), a three-equation random effects system for count data with endogenous ordered and continuous variables. The notation in the main text does not reflect the differing frequency of observation in the data. The accident counts for the first equation and the car weights in the third equation are observed each quarter. The mobile phone usage variables y_2 are observed yearly and the time subscript for u_{2it} and ε_{2it} is for the calendar years in the sample (2001 and 2002). Collect the random effects into column vectors $u_{2i} = (u_{2i1}, u_{2i2})'$ and $u_{3i} = (u_{3i1}, \ldots, u_{3i4})'$ and define $u_{1i} = \alpha_{1i}$. Here the likelihoods are derived for all four quarters of data; in implementation the likelihood is modified appropriately for missing quarters of data. Define $u_i = [u_{1i}, u'_{2i}, u'_{3i}]'$. Then var (u_i) is

$$\text{var}\,[u_i] = \begin{bmatrix} \sigma_1^2 & \rho_{12}\sigma_1\iota_2 & \rho_{13}\sigma_1\sigma_3\iota_4' \\ \rho_{12}\sigma_1\iota_2 & I_2 + \sigma_2^2\iota_2\iota_2' & \iota_2\iota_4'\rho_{23}\sigma_2\sigma_3 \\ \rho_{13}\sigma_1\sigma_3\iota_4 & \iota_4\iota_2'\rho_{23}\sigma_2\sigma_3 & \tau^2 I_4 + \sigma_3^2\iota_4\iota_4' \end{bmatrix}$$

$$\equiv \begin{bmatrix} \Sigma_{u11} & \Sigma_{u12} & \Sigma_{u13} \\ \Sigma_{u21} & \Sigma_{u22} & \Sigma_{u23} \\ \Sigma_{u31} & \Sigma_{u32} & \Sigma_{u33} \end{bmatrix}$$

where ι_k is a k-row column vector of ones and I_k is a k-rank identity matrix.

The observed data for an individual is $y_{1i} = (y_{1i1}, \ldots, y_{1i4})'$, $y_{2i} = (y_{2i1}, y_{2i2})'$, $y_{3i} = (y_{3i1}, \ldots, y_{3i4})'$. To simplify notation, drop the i subscripts from here on. The joint density of the data conditional on u_1, $f(y_1, y_2, y_3 \mid u_1)$, is

$$f(y_1, y_2, y_3 \mid u_1) = f(y_2, y_3 \mid u_1)\, f(y_1 \mid y_2, y_3, u_1)$$

where

$$f(y_2, y_3 \mid u_1) = f(y_3 \mid u_1)\int f(y_2^* \mid u_1, y_3)\,dy_2^* \qquad \text{(A.1)}$$

$$f(y_3 \mid u_1) = \phi_4\left(\beta_3' x_3 + \frac{\rho_{13}\sigma_3}{\sigma_1}\alpha_1 \iota_4, \tau^2 I_4 + [1-\rho_{13}^2]\sigma_3^2 \iota_4 \iota_4'\right) \tag{A.2}$$

$$f(y_2^* \mid u_1, y_3) = \phi_2(AB^{-1}C, \sum u_{22} - AB^{-1}A') \tag{A.3}$$

$$A \equiv \begin{bmatrix} \Sigma_{u21} & \Sigma_{u23} \end{bmatrix}$$

$$B \equiv \begin{bmatrix} \Sigma_{u11} & \Sigma_{u13} \\ \Sigma_{u31} & \Sigma_{u33} \end{bmatrix}$$

$$C \equiv \begin{bmatrix} u_1 & y_3 - \beta_3' x_3 \end{bmatrix}'$$

$$f(y_1 \mid y_2, y_3, u_1) = \prod_{t=1}^{4} \frac{\exp(-s\lambda_t)(s\lambda_t)^{y_{1t}}}{y_{1t}!}$$

$$\lambda_t = v_t \exp(\beta_1' x_{1t} + \gamma' y_{2t} + \delta y_{3t})$$

All densities are to be read as conditional on the x covariates. The limits of the rectangular integration region in (A.1) are the appropriate κ's for the value of y_{2t} for year 1 and year 2, based on (6). In (A.2) and (A.3), $\phi_p(\mu, \Sigma)$ is the p.d.f. of a p–variate normal *r.v.* with mean vector μ and covariance matrix Σ. If the individual does not have a mobile phone in any period in a year, there is no selection equation for minutes of usage and the integral pertaining to that year in (A.1) drops out.

The likelihood for the data is then found as (11), where the integral there can be written

$$\int_{-\infty}^{\infty} f(y_1, y_2, y_3 \mid u_1) \frac{1}{\sigma_1} \phi\left(\frac{u_1 + \sigma_1^2/2}{\sigma_1}\right) du_1$$

This integral is evaluated for each i by Gauss-Hermite quadrature with 16 evaluation points. MLE is performed using the BFGS variant of the DFP algorithm with numerical derivatives in FORTRAN.

When y_2 represents hands-free device usage, minor modifications are required. First, the hands-free usage question is asked once for all quarters, so a period-specific error in (8) is redundant with α_{2i} and ε_{2it} is dropped. Furthermore, with a single observation per individual on y_2, the integral in (A.1) becomes unidimensional and σ_2 is no longer identified and is fixed to unity. Finally, if the individual does not use a mobile phone while driving in any period, there is no selection equation for hands-free device usage and the integral in (A.1) drops out.

A.2 LR Tests of the Parametric Models

The likelihood ratio tests of the parametric models mentioned in the text are non-standard because they involve parameters on the boundary of the parameter space and because some of the nuisance parameters appear only under the alternative hypothesis. The null hypothesis for the tests for the ML models is H_0: $\sigma_1 = \sigma_3 = 0$ vs. H_A: $\sigma_1 > 0$, $\sigma_3 > 0$, $\rho \equiv (\rho_{12},\rho_{13},\rho_{23}) \in (-1,1)^3$. Under the null, σ_1 and σ_3 are on the boundary of the parameter space and ρ is a nuisance parameter that appears only under the alternative. Test statistics with parameters appearing only under the alternative hypothesis have complicated distributions in general (Andrews, 2001), whereas parameter-on-the-boundary (PB) problems with all parameters appearing both under the null and the alternative hypotheses generally lead to simpler distributions. Using techniques from King and Shively (1993), we therefore transform this test through reparameterization into a simpler PB problem so that the test statistic is a mixture of chi-squares. Appendix B.11 in Hahn and Prieger (2006a) contains details.

A.3 NLIV and Random Coefficients

The moment condition (3) for NLIV is still valid if the usage coefficients are random, as modeled in Hahn and Prieger (2006b). In that case, driver i's vector of coefficients for mobile phone usage is $\gamma_i = \bar{\gamma} + \eta_i$ where $\bar{\gamma}$ is the mean coefficient vector and η_i is a scalar that represents i's departure from the average mobile phone coefficients. Because η_i is scalar, the randomness in the usage effects is symmetric across usage classes. Then (2) can be written s $\exp(\beta' x_{it} + \bar{\gamma}' y_{2it} + \delta y_{3it})\zeta_{it}$, with $\zeta_{it} = \xi_{it}\exp(\eta_i d_{it})$, where d_{it} is an indicator that usage is not in the excluded category. If instead of $E(\xi|z) = 1$ the slightly stronger assumption that $E(\xi\exp(\eta d)|z) = 1$ is satisfied, then $E(\zeta|z) = 1$ and moment condition (3) is valid with ζ replacing ξ. The assumption requires that not only are deviations from an individual's mean of y_2 over time not systematical related to the individual-specific error v, they are also unrelated to the individual-specific random part of the coefficient, η. Given that both v and η are time-invariant, they both reflect the driver's type, and it is reasonable to assume that the same instruments are valid for both. If this assumption is not satisfied, it would (in principle) be detected by the overidentification tests reported in Table 3.

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Table 1: Estimates of the Proportion of Drivers Using Mobile phones and Hands-Free Devices while Driving

	Authors' survey		Other sources surveyed in Hahn and Prieger (2006b)
	Raw average *Oct 2001—Sept 2002*	**Weighted average** *Oct 2001—Sept 2002*	*Nov 2000—Nov 2003*
% of drivers who use a mobile phone while driving, out of…			
All Drivers	73	64	30-59
Drivers who Have a Mobile phone	86	82	43-89
% of drivers who use HF device while driving, out of…			
All Drivers	30	28	23
Drivers who Have a Mobile phone	41	44	28

Table notes: In the authors' survey, figures for mobile phone use are the percentage of the respondents who chose an answer other than "none" to "During [the time period in question], how many minutes did you typically talk on your mobile phone while driving?" Weighted average is calculated using survey weights.

Table 2: Accidents: Poisson Estimations

	Estimation 1		Estimation 2	
	IRR	*P*-value	IRR	*P*-value
Men: have phone, no use	1.073	0.839	1.243	0.525
Men: 1-15 mins/week,	1.134	0.651	1.054	0.853
Men: 2-20 mins/day	0.899	0.757	0.726	0.380
Men: 20-60 mins/day	1.232	0.598	0.995	0.991
Men: > 1 hr/day	0.204	0.133	0.212	0.147
Women: have phone, no use	0.705	0.279	0.753	0.405
Women: 1-15 mins/week,	1.273	0.282	1.168	0.492
Women: 2-20 mins/day	1.898**	0.016	1.323	0.298
Women: 20-60 mins/day	3.269***	0.000	2.212***	0.008
Women: > 1 hr/day	3.714***	0.001	2.591**	0.018
Men: hands-free some	1.506*	0.096	1.240	0.396
Men: hands-free always	1.202	0.473	1.076	0.788
Women: hands-free some	0.973	0.886	0.890	0.543
Women: hands-free always	0.520***	0.006	0.494***	0.003
Female	0.759	0.353	0.883	0.679
Car weight (log)			0.533**	0.028
Married			0.721**	0.013
Children in household			1.213	0.130
Age			0.904***	0.000
Age Squared			1.001***	0.000
Income (log)			1.005	0.952
Work Full Time			1.472***	0.005
Miles driven (log)			1.138	0.112
Commute time (log)			1.153**	0.018
Rural freeways			0.830	0.283
Urban surface streets			1.142	0.305
Rural surface streets			0.592	0.130
Area pop. density (log)			1.097	0.120
Area commute time (log)			1.208	0.741
Precipitation days			0.993	0.687
Snow days			0.976**	0.046
Days below freezing			0.996	0.528
Hours of light daily			0.602**	0.021
Average mobile phone IRR	1.303		1.050	
χ^2 statistic (dof)	95.6 (57)	0.001	229.8 (75)	0.000
Log likelihood	-1854.93		-1703.66	
N	26,572		25,243	

* and ** denote significance at the 5%, and 1% level, respectively.

Notes: Dependent variable is the quarterly traffic accident count for an individual. Both specifications include quarter and state fixed effects. Sample covers Q4 2001—Q3 2002. Excluded mobile phone dummy is “no phone”. IRR is estimate of the incident risk ratio, exp(β). *P*-values based on standard errors robust to heteroskedasticity and clustering on individuals. *Average mobile phone IRR* is the average IRR from the mobile phone and hands-free device variables, weighted by the number of drivers in each phone and hands-free device category.

Table 3: Accidents: Poisson and IV Estimations (Female Sample)

	Estimation 3 (Poisson)		Estimation 4 (IV)	
	IRR	*P*-value	IRR	*P*-value
Women:				
Have phone, no use	0.776	0.450	1.042	0.940
Use phone 1-15 mins/week	1.193	0.465	1.130	0.780
Use phone > 15 mins/week	1.646*	0.064	1.187	0.750
Hands-free device: some	0.909	0.632	0.635	0.185
Hands-free device: always	0.525**	0.015	0.729	0.504
Car weight (log)	0.417**	0.017	7.373***	0.006
Married	0.685**	0.020	0.639	0.127
Kids in household	1.189	0.309	0.980	0.955
Age	0.307***	0.000	0.189**	0.015
Age squared	1.125***	0.001	1.179**	0.028
Income (log)	1.086	0.567	0.941	0.808
Work full time	1.515**	0.020	1.429	0.232
Miles driven (log)	1.156*	0.088	1.193	0.132
Commute time (log)	1.077	0.391	1.121	0.469
Rural freeways	0.929	0.728	0.979	0.957
Urban surface streets	0.956	0.798	0.846	0.604
Rural surface streets	0.603	0.251	0.385	0.115
Area pop. density (log)	1.134*	0.092	1.169	0.268
Area commute time (log)	0.654	0.539	0.499	0.597
Precipitation days	0.996	0.814	0.978	0.521
Snow days	0.987	0.533	0.938**	0.030
Days below freezing	0.993	0.236	0.999	0.945
Hours of light daily	0.885**	0.038	0.916	0.430

	distribution	statistic	*p*-val	distribution	statistic	*p*-val
χ^2 statistic (Wald test)	$\chi^2(24)$	1,661.0	0.000	$\chi^2(24)$	1069.5	0.000
OverID test statistic 1 (*F*)				$F(16,16936)$	1.05	0.598
OverID test statistic 2 (*J*)				$\chi^2(16)$	21.6	0.156
OverID test statistic 3 (C_1)				$\chi^2(3)$	2.44	0.487
OverID test statistic 4 (C_2)				$\chi^2(4)$	7.00	0.135
Exogeneity test statistic 1				$\chi^2(23)$	64.7	0.000
Exogeneity test statistic 2				$\chi^2(5)$	29.2	0.000
N		16,961			16,961	

*, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Notes: Dependent variable is the quarterly traffic accident count for an individual. Standard errors, *p*-values, and test statistics are robust to heteroskedasticity and clustering on individuals, except for *OverID test statistic 1*. Neither specification includes time or state fixed effects. The *Wald test* is for the joint significance of all coefficients. Each *OverID test statistic* tests the null hypothesis that the identifying instruments are uncorrelated with the error term and are correctly excluded from equation (2). Statistic *F* assumes homoskedastic errors. Statistic *J* is Hansen's J statistic and is robust to heteroskedasticity and clustering on individuals. Statistic C_1 tests only the mobile phone usage instruments and statistic C_2 tests only the instruments for car weight. The *Exogeneity test statistics* are for the Hausman test that the mobile phone, hands-free, and vehicle weight variables are exogenous. Hausman test statistics are with reference to Estimation 3. Hausman statistic 1 tests all coefficients except the constant; statistic 2 tests only the coefficients for the variables treated as endogenous. See also notes to Table 2.

Table 4: Accidents, Hands-free Device Usage, and Vehicle Safety: Three Equation MLE

		Small set of instruments				Large set of instruments			
		Estimation 5 Men		Estimation 6 Women		Estimation 7 Men		Estimation 8 Women	
Coefficient and Variable		IRR	*P*-value	IRR	*P*-value	IRR	*P*-value	IRR	*P*-value
β_1	Have phone, no use	1.230	0.632	0.741	0.418	1.232	0.627	0.735	0.405
β_1	Use phone 1-15 mins/week,	0.809	0.539	1.005	0.988	0.831	0.584	1.035	0.907
β_1	Use phone 2-20 mins/day	0.498	0.162	1.115	0.776	0.516	0.154	1.163	0.681
β_1	Use phone 20-60 mins/day	0.621	0.423	1.745	0.201	0.654	0.437	1.858	0.136
β_1	Use phone > 1 hr/day	0.126*	0.084	1.488	0.594	0.133*	0.086	1.626	0.502
γ_1	Hands-free device: some	1.949	0.300	1.670	0.522	1.900	0.210	1.456	0.573
γ_2	Hands-free device: always	2.583	0.319	1.246	0.862	2.455	0.216	1.001	0.999
δ	CarWgtLn	0.044	0.286	0.278	0.622	0.061	0.169	0.753	0.833
	Other controls as in RF3	yes		yes		yes		yes	
	Average mobile phone usage IRR	1.172				1.141			
		parameter		*parameter*		*parameter*		*parameter*	
σ_1^2		0.759	0.255†	0.666*	0.071†	0.684	0.173†	0.630*	0.061†
ρ_{12}		-0.544***	0.002	-0.658	0.408	-0.587***	0.000	-0.540	0.471
ρ_{13}		0.774***	0.000	0.140	0.857	0.766***	0.000	-0.192	0.650
	LR statistic	1.68E04	0.000	3.61E04	0.000	1.66E04	0.000	3.54E04	0.000
	Log likelihood	7,516.5		16,597.8		7,557.6		16,752.0	
	# individuals	2,256		4,612		2,256		4,612	
	# observations	8,144		16,720		8,144		16,720	

†One sided *p*-value.

*, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table notes: Dependent variables are the quarterly traffic accident count for an individual, hands-free device category of usage, and log vehicle weight. LR statistic is the likelihood ratio statistic for test H_0: $\sigma_1^2 = \sigma_3^2 = 0$ vs. H_A: $(\sigma_1^2, \sigma_3^2) > 0$, $(\rho_{12}, \rho_{13}, \rho_{23}) \in (-1,1)^3$. It has a non-standard distribution; see the appendix for details. Estimated but not reported: the rest of β_1 (for the other controls included as in Estimation 2 [including time fixed effects but with region indicators replacing state fixed effects]) and $(\beta_2, \delta, \kappa)$. Likelihood is calculated via Gauss-Hermite quadrature (see the appendix). The standard errors account for the panel structure of the data. *Average mobile phone usage IRR* is the average IRR from the mobile phone and hands-free device variables, weighted by the number of drivers in each phone/hands-free device category. See notes to Table 2 on IRR.

Figure 1: Factors Affecting Collision Risk (Model 1)

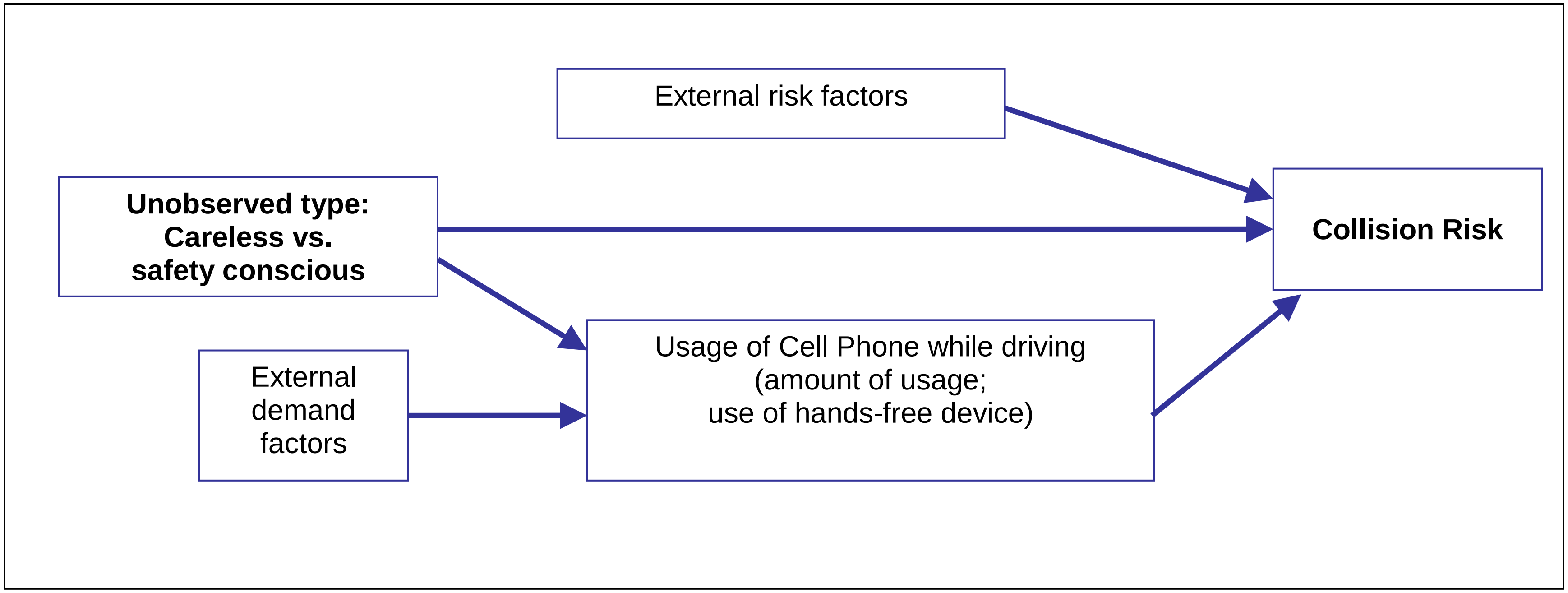

Figure 2: Yearly Accident Rates in the Sample