Health Insurance, Treatment and Outcomes:
Using Auto Accidents as Health Shocks*

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Abstract:

Previous studies find that the uninsured receive less health care than the insured, yet differences in health outcomes have rarely been studied. In addition, selection bias may partly explain the difference in care received. To examine health outcomes and deal with selection problems, this paper focuses on an unexpected health shock—severe automobile accidents where victims have little choice but to receive treatment. Another innovation is the use of a comparison group that is similar to the uninsured: those who have private health insurance but do not have automobile insurance. The medically uninsured are found to receive twenty percent less care and have a higher mortality rate compared to patients with health insurance. It appears that the ability-to-pay of patients has a significant effect on treatment decisions and the additional treatment yields large improvements in health outcomes.

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1. Introduction

Recent efforts to reform the $1.3 trillion U.S. healthcare industry are often motivated by a concern that the uninsured are denied access to health care (NCHS, 2002). Indeed, theory suggests that health care providers would offer less treatment to the uninsured if they were unable to pay for care. Previous empirical work supports this conclusion and finds that the uninsured receive approximately forty percent less health care than the insured.[1]

However, these estimates can be difficult to interpret. First, health outcomes are rarely compared. Without knowing the effect on health, treatment differences may imply that the insured receive too much care, as opposed to the uninsured receiving too little. For example, moral hazard problems may allow physicians to practice what has been labeled 'flat-of-the-curve medicine'—a phrase attributed to Enthoven (1980) that implies small improvements in health outcomes with additional treatment. While the insured may receive more treatment, this may not translate into health differences.

Further, there may be selection problems. Individuals decide to purchase insurance and they decide to seek medical care. If those with a low risk of using medical care are also less likely to purchase insurance, then treatment differences may have little to do with access to care. This positive correlation between risk level and insurance coverage is a standard result in contract theory and suggests that information problems in insurance markets may lead to treatment differences. The empirical work is further complicated by the lack of an adequate comparison group to test whether unobserved differences between the insured and uninsured are driving the difference in care received.

[1] Estimates center around forty percent less care for the uninsured. See, for example, Currie & Gruber (1997), Currie and Thomas (1995), Haas and Goldman (1994), Long, Marquis, and Rodgers (1997), Spillman (1992), and Tilford et. al. (1999). Marquis and Long (1994) and Brown (1998) offer reviews.

To examine health outcomes and deal with selection problems, this paper focuses on an unexpected health shock—severe automobile accidents where incapacitated crash victims have little choice but to use professional medical care. Using a unique data set that links police accident reports to hospital discharge records, treatment levels and mortality rates are compared between the insured and uninsured. These data provide a complete picture of each accident and offer a new way to investigate whether the uninsured are denied access to life-saving health care. One innovation in the paper is the use of a comparison group that is similar to the uninsured in terms of risk taking behavior, income, and other characteristics: drivers who have health insurance but who do not have *automobile* insurance.

The focus on severe automobile accidents has a number of advantages. First, police record mortality, which allows a comparison of health outcomes. The few studies that have looked at inpatient outcomes find mixed evidence of insurance effects (Ayanian et.al. (1993), Currie & Gruber (1997), Haas and Goldman (1994), Hadley et. al. (1991), Sada et.al. (1998)). However, these papers do not always control for differences in the illnesses suffered by the uninsured, while others rely on composite measures of physician diagnoses and procedures to control for illness severity. These measures will depend on insurance status if the uninsured were offered less care. In contrast, this paper uses more objective severity measures such as police-reported injuries and crash characteristics.[2] In addition, while previous papers did not control for differences in the hospitals used by the insured and uninsured, this paper exploits within-hospital variation in treatment and outcomes to explicitly control for hospital characteristics that do not vary across patients, such as hospital resources and accounting procedures.

Second, contact with professional health care providers is virtually automatic for severe accidents, as ambulances arrive as part of the crash investigation. When dealing with other health problems, the uninsured may be less likely to seek care due to underlying differences in health risks or preferences. Here, the public nature of the health problem ensures that patients receive medical attention. In addition, previous papers were unable to control for the time patients wait to visit the hospital. The focus on severe crashes allows a comparison of treatment and outcomes from the moment the health problem begins.

Third, severe accidents are largely unexpected at the time of the health insurance purchase decision, as opposed to the chronic conditions that are usually studied (Brown, 1998). Patients live with chronic health problems and gain private information about future health care use. These are cases where adverse selection problems are at their most extreme, as those likely to use health care may be more likely to purchase insurance. This selection into insurance based on the unobserved propensity to use health care confounds the interpretation of treatment differences. However, if the decision to purchase insurance were not based on the likelihood of being in a severe automobile accident, then the approach taken here would largely avoid this selection problem.

Finally, automobile accidents are a particularly important health problem for the uninsured. Most health problems are common to older individuals who are almost universally insured. In contrast, the uninsured tend to be younger, and automobile accidents are the leading cause of death among those under the age of thirty-five (CDC, 1998).

The results suggest that the uninsured receive twenty percent less treatment than the privately insured, controlling for personal, crash, and hospital characteristics. While this

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[2] Haas and Goldman (1994) also study emergency care. However, they include all types of emergency care, and it appears that the case mix is substantially different between the insured and uninsured in ways that are not controlled.

represents a substantial difference, it is smaller than the previous findings, suggesting that selection bias may be important. The uninsured are also found to have a higher mortality rate—an increase of 1.4 percentage points from the mean mortality rate of 3.8%. A number of specification and robustness tests suggest that unobserved differences between the insured and uninsured are not driving the treatment and mortality differences. For example, drivers who do not have *automobile* insurance are similar to those without health insurance; yet automobile insurance status does not predict treatment or health outcomes.

The structure of the paper is as follows. Section two briefly presents theoretical considerations and their implications for interpreting the results. Section three describes the data and presents mean comparisons of treatment, mortality, and crash characteristics between the insured and uninsured. Section four presents the empirical estimates, where within-hospital variation is used to test the effect of insurance status on treatment and mortality. Section five demonstrates the robustness of the results. Section six discusses implications of the findings, and section seven concludes.

2. Theory

At the time of an accident, insurance lowers the price of health care faced by the insured and raises the effective price that providers can collect. Both factors suggest that the insured will receive more treatment. The overall effect of insurance on treatment decisions, and ultimately health outcomes, is a combination of these supply and demand factors. However, when previous estimates compared treatment levels between the insured and uninsured, they may have overstated the insurance effect. In particular, we have to consider the demand for insurance and how the insured may differ from the uninsured.

In addition, the paper does not control for differences in hospital characteristics and times-to-diagnosis.

Demand-side

Consider first the demand for insurance. Those who have a high risk of using health care may be more likely to purchase insurance. This positive correlation between risk and insurance coverage, due to adverse selection and/or moral hazard problems, is a standard result from contract theory (Chiappori and Salanie, 2000; Chiappori et. al. 2001). For example, consider a simple two-period model of insurance demand where there are two states of the world in the second period: healthy and sick. Further, consider two types of consumers categorized by their probability of becoming sick. In the first period, they maximize expected utility and can use market insurance to allocate resources to different states of the world. These models suggest that if insurance premiums were actuarially fair, then risk-averse consumers would fully insure. However, due to information problems, or other frictions, insurance premiums may not be actuarially fair. One way for insurance companies to overcome information problems is to price insurance packages, comprised of different deductible and co-payment combinations, in such a way that the choice of a particular package reveals the type of consumer: a separating equilibrium. It can be shown that in this environment only the most likely to suffer the sick state will be fully insured (Rothschild and Stiglitz, 1976). Chiappori et. al. (2001) have generalized this result of a positive correlation between risk and insurance to a number of environments, including the co-existence of moral hazard and asymmetric information problems.

In addition, agents will also differ with respect to tastes and income. Perhaps the most interesting difference for this current study is that individuals with a relatively high degree of risk aversion may be more likely to both purchase insurance and drive safely. This suggests the potential for a negative correlation between insurance coverage and health risk if safer drivers sustained less severe injuries. Dealing with the potential for heterogeneity in risk preference is a focus of the empirical section below.

Further, the demand for health care will depend on insurance status. Those with insurance face a lower price for health care at the time of an illness—only a deductible and co-payment. This implies that they will be more likely to visit a doctor once ill, all else equal. One caveat is that by the time the uninsured do visit a hospital, their illnesses may be more severe. Previous work has estimated the probability that an individual will make a "health care contact" multiplied by the difference in treatment once contact has been made. In the cases studied here, the decision to visit the hospital is largely out of the control of the patient as police or witnesses call for medical professionals.

Supply-side

There is a literature that considers the effect of reimbursement rules on treatment decisions, begun by McGuire and Ellis (1986). Treatment decisions by health care providers are modeled, abstracting from the decisions of patients. Physicians choose treatment levels to maximize an objective function that includes both profits and the benefits of treatment to patients. This model suggests that an increased ability-to-pay, through insurance for example, would result in greater treatment. Imbedded in these models is the notion that providers may offer more care to the insured due to moral hazard problems. However, these results do not depend on profits being part of the objective function. If profits were incorporated into a resource constraint, where greater treatment of insured patients provides resources to treat both insured and uninsured patients, then the prediction of more treatment for the insured would remain.

Another factor affecting the supply response is whether providers know the patient's insurance status. In fact, it appears that one of the first pieces of information discovered is insurance status. Medical professionals search patients to find not only insurance information, but medical and emergency contact information as well. Insurance companies regularly recommend that consumers carry their insurance card especially for this type of situation. Once known, the expected payer is reported on the patient's chart. When treatment decisions are made, insurance status is likely known.

Finally, treatment differences may be smaller given the legal ramifications of refusing to treat patients. For example, federal law mandates that hospitals stabilize trauma patients. However, treatment differences after stabilization are predicted.

Welfare implications

Both supply and demand factors tend to suggest that the insured will receive more treatment. However, the welfare implications are less straightforward. Treatment differences may be efficient in a number of environments. For example, the uninsured may not value additional treatment as much as the insured, as suggested by the choice to purchase insurance. Consider the standard planner's problem where each person is weighted equally. The optimal consumption profile is such that the marginal utility of consumption is equated across individuals. In models of insurance demand, those who expect a higher marginal utility of consumption when sick are more likely to purchase insurance. If the insured had a higher marginal utility of consumption when sick, then the insured would require greater treatment levels to equate marginal utilities.[3]

[3] There are other environments where treatment differences may be efficient. For example, if no treatment differences were present, the risk of financial losses alone may not be enough to induce the purchase of insurance and the optimal amount of risk sharing. In addition, if it were too costly for the uninsured to reveal their type as

One case where inefficiencies are more easily tested is the case of overutilization by the insured. Consider a health production function that maps treatment into health benefits. It has been argued that at the advanced state of technology in the U.S., diminishing returns have resulted in physicians practicing 'flat-of-the-curve' medicine. That is, the insured may receive more care, but that may have little effect on health outcomes. In this case, the marginal benefit of treatment is close to zero, which is less than the positive marginal cost, and welfare implications stem from distorted insurance prices. However, if the additional treatment received by the insured were useful in improving patient outcomes, then observed differences in treatment may represent underutilization by the uninsured, overutilization by the insured, or both.

Supply and demand factors largely suggest that the uninsured will receive less treatment. If health were increasing in treatment, conditional on injury severity, then the insured would have better outcomes as well. However, if a positive correlation between risk and insurance coverage were due to private information problems in insurance markets, then self-selection into insurance markets would contaminate treatment and health outcome comparisons (Heckman, Lalonde, and Smith, 1999). As opposed to the chronic conditions usually studied, where private information problems are likely at their most extreme, this paper conditions on an unexpected health shock to mitigate the effect of this selection problem.

3. Data Description

The Crash Outcome Data Evaluation System (CODES) offers a unique data set to compare patients following an automobile accident. CODES links police accident reports with hospital discharge records using identifiers such as patient name, birth date, and time of accident.

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particularly unlikely to use health care, then the uninsured may be willing to take the risk of large medical bills and potentially inferior treatment instead of paying the insurance premium.

The National Highway Traffic Safety Administration subsidized individual state efforts to link these two sources of data, and, until now, they have only been used to study highway safety (NCSA, 1998).

This paper uses data from Wisconsin for the period 1992 through 1997.[4] In Wisconsin, all police accident reports are submitted to the Wisconsin Department of Transportation, and all inpatient hospital records are submitted to the Wisconsin Department of Health and Family Services. Analysts at the Center for Health Systems Research and Analysis (CHSRA), located at the University of Wisconsin at Madison, linked these data in an effort to improve traffic safety research.

According to CHSRA, approximately 80% of all crash-related hospitalizations were linked successfully. Patients who die at the scene of the accident do not make it into the inpatient data, so it is not possible to identify the health insurance status of these victims. As a result, mortality comparisons are done after patients reach the hospital. Other reasons for linkage failure include the following: the patient was transported out of Wisconsin, the crash was not reported to the police, or the crash record contained insufficient identifying information. For the severe accidents investigated here, the proportion of matches is likely to be even higher than 80%. For example, severe crashes are more likely to be reported and information, such as the time of the accident, is more likely to be known for ambulance transfers. In any case, it appears that the likelihood of linkage failure is unrelated to health insurance status.[5]

The police-report data offer a complete picture of each accident. Characteristics such as age, sex, seat location, seat belt use, entrapment in the vehicle, and injury severity are available.

[4] Wisconsin is one of the original CODES states and the only state that regularly supplies a public-use data set. All 23 CODES states were contacted. Most of the other states are still in the process of linking the data or did not have key variables of interest.

Wisconsin Police report injury severity according to the KABCO score: Killed; A, B, or C injuries consisting of incapacitating injuries, non-incapacitating injuries, or possible injuries; and other or unknown. At the accident scene, a police officer records the injury category. If the crash victim later died due to the accident, then the injury severity was scored as a K—even if the death occurred after hospital discharge.[6] Other crash characteristics include vehicle damage, road condition, and the types of crashes, vehicles, and roads. Also, population size where the accident occurred is reported.

Police-reported crash and personal characteristics offer a new way to control for injury severity when comparing treatment levels and outcomes between the insured and uninsured. Previous empirical work used composite measures of diagnoses and procedures to control for injury severity. However, if the uninsured were offered less treatment as theory suggests, then they would be categorized as having less severe injuries, which would distort comparisons. In contrast, police have little incentive to care about the patient's ability-to-pay hospitals when determining injury or crash severity. By conditioning on crash characteristics, injury severity is controlled by comparing patients who were in similar accidents. For example, a patient who crashed on a rural highway resulting in severe vehicle damage will have greater injuries compared to a patient who crashed on a slower moving urban street. Of course, hospital data can be used to supplement the police measures of injury severity.

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[5] CHSRA data documentation argues that "there is no reason to expect that the cases not linking are different from cases which do link."

[6] The scores of K are the raw data for the often-used Fatality Analysis Reporting System (FARS) distributed by the National Highway Traffic Safety Administration. It is generally regarded as 'thirty-day mortality' meaning that deaths up to thirty days from the accident are recorded in the police data, though deaths after thirty days are also recorded. For a small number of cases the patient died in the hospital and the KABCO score does not equal K. These have been coded as fatal injuries in the analysis, though results are not sensitive to this definition. As noted above, those who die at the scene do not enter the inpatient data. The severity of injury at the time of entry into the hospital is explored more fully below.

The hospital discharge data also provide a rich set of variables. These include a hospital identifier, measures of treatment, such as total facility charges and length of stay, and codes for procedures and diagnoses. The total facility charges represent the standard room and procedure charges as opposed to what is billed to insurance companies or the government. This is particularly useful for research purposes, as charges are uniform across insurance plans within each hospital. Major diagnostic categories are used to compare patients with similar types of injury, such as nervous system or musculoskeletal injuries.

Finally, the expected payer is reported. As in previous work, "uninsured" is defined as having the expected payer identified as self-pay as opposed to a form of private insurance or government program. While the uninsured may be partially insured through subsequent lawsuits or through automobile insurance, these are uncertain payments that hospitals do not look to first. The hospital would have to judge the probability that another driver caused the accident times the probability that the other driver has liability insurance, in which case the hospital may receive payment much later.[7] In addition, medical insurance within automobile insurance contracts is usually capped at a low payment level, such as $2500—far below the costs of care in these severe crashes. Meanwhile, the patients chart will note the lack of insurance as opposed to this partial coverage. It appears, then, that hospitals would regard the uninsured as likely candidates for uncompensated care, while the partial coverage will make finding treatment differences for the uninsured more difficult.

The total number of linked police-hospital records is 28,236 and ten percent are uninsured. This fraction is similar to the estimated 9-11% of the non-elderly population who are

[7] Much of hospital bad debt is due to catastrophic events to uninsured patients, suggesting they often do not get paid. In addition, Wisconsin is not a no-fault insurance state. That is, reimbursement from an insurance company would require proving that another driver was at fault. Also, at the time of these crashes, Wisconsin was one of the few states that did not require automobile policies to include liability insurance.

uninsured in Wisconsin over this period (KFF, 1998). I restrict the sample in a number of ways, though results are similar when the entire data set is used as shown below. First, to focus on cases where patients are the least likely to make treatment decisions, the estimation focuses on patients who were the most severely injured: those who were judged by the police to be incapacitated and those who eventually died.[8] This results in 16,648 observations. In addition, patients over the age of sixty-five are excluded due to near universal insurance coverage through Medicare. Also, hospital records are available for patients where they were finally discharged, so patients who transferred from another hospital will mechanically have shorter lengths of stay. These observations are dropped for comparability, though insurance status does not predict hospital transfer.[9] It does not appear that hospitals transfer the financial risk of treating uninsured patients to other hospitals. Finally, comparisons are first restricted to the uninsured and the privately insured. Comparisons with Medicaid recipients are made separately. These restrictions result in 10,962 patients to study, of which nearly fifteen percent are uninsured.[10]

Table 1 displays the wide set of personal and crash characteristics that are available in the CODES data, and compares the uninsured with the privately insured. The basic results are shown in the first three rows: the uninsured receive less treatment and have higher mortality, on average. They stay in the hospital for 6.5 days, compared to 9.2 days for the insured, a thirty-percent difference. Similarly, average facility charges are $13,400 versus $20,700. Median

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[8] According to the National Safety Council's 1996 *Manual on Classification of Motor Vehicle Traffic Accidents*, an incapacitating injury is "any injury, other than a fatal injury, which prevents the injured person from walking, driving or normally continuing the activities the person was capable of performing before the injury occurred. Inclusions: severe lacerations, broken or distorted limbs, skull or chest injuries, abdominal injuries, unconsciousness at or when taken from the accident scene, and unable to leave the accident scene without assistance, and others. Exclusion: momentary unconsciousness". It appears that almost all of those with fatal injuries were incapacitated at the scene as evidenced by their nearly universal rate of ambulance transfer.

[9] In a regression predicting hospital transfer with full controls, an indicator of having health insurance has a coefficient of –0.002 with a standard error of 0.004.

[10] The restrictions dropped 2,113 observations due to age. 763 observations were dropped due to transfer. There were 2,081 observations where the patient has Medicaid or other government insurance. Medicaid recipients will be

differences are smaller, though still substantial: 4 days in care for the uninsured and 5 days for the insured, while the median facility charges are $6,800 compared with $9,000.[11] In addition, the mortality rates are 4.4% for the uninsured compared with 3.7% for the insured.

Table 2 shows that these treatment and mortality differences remain within police-reported injury severity levels. The table also shows that total facility charges increase with injury severity, suggesting that police evaluations are informative. Also, the difference in treatment is larger for more severely injured patients. However, patients with possible or unknown injuries are more likely to choose whether to visit the hospital. Selection of the relatively healthy uninsured victims out of the hospital data may contribute to the smaller treatment differences found in these categories. Alternatively, there may be less discretion in these types of cases, as they often involve broken bones that may require similar procedures for both the insured and uninsured.

Apart from treatment and mortality differences, Table 1 shows that there are other differences between the insured and uninsured, as expected. The uninsured are slightly younger (29 vs. 30) and more likely to be male (72% vs. 62%). Perhaps surprisingly, they are less likely to use some form of restraint (a seat belt or child seat) compared to the insured (19% vs. 30%), consistent with differences in seat belt use found by Clyde et.al. (1996). It appears that the uninsured are less risk averse, as they are willing to risk the potential for more expensive hospital bills associated with not wearing a seat belt. The uninsured also drive slightly older cars that are less likely to have an airbag deployment. While these comparisons suggest that the uninsured may suffer more severe injuries, they are less likely to have a diagnosis of multiple significant

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examined in section five. 624 observations were lost due to missing values, and 105 observations were dropped due to few observations within a hospital.

trauma (16% vs. 20%), or to be trapped at the scene (15% vs. 17%)—both predictors of mortality.[12]

Note that conditioning on incapacitation at the scene does not mean that patients will have similar observable characteristics. Indeed, if getting into an incapacitating accident were completely random, then the differences in the population, such as age or inclination to wear a seatbelt, would be revealed in the incapacitation sample. Much of the paper attempts to control for these differences, including the use of a particularly rich set of control variables, patients who do not have automobile insurance as a comparison group, and a number of other specification tests reported in section five.

There are some similarities between the two groups. Three major diagnosis categories stand out for both: musculoskeletal system and connective tissue, nervous system, and multiple significant trauma. Both groups come largely from rural areas. In addition, vehicle damage and vehicle types are also similar for the two groups.

4. Empirical Model and Results

The mean differences in treatment and mortality are suggestive. However, conditioning on observable crash and personal characteristics provides a way to compare patients with similar injuries. Further, hospital fixed effects are used to exploit within-hospital variation in treatment. In this way, hospital characteristics that are constant across patients, such as accounting procedures, charity care policies, and trauma resources, are controlled. In addition, year fixed

[11] As the median and mean comparison shows, the treatment measures are right skewed, as usual. In the panel regressions used below, the natural logarithm of each treatment measure is used to place less weight on the extreme observations. In addition, the results are shown to be robust to trimming the data of large and small observations.

[12] While the major diagnostic categories are used to compare patients with similar areas of injury, the smaller proportion of uninsured patients with multiple significant trauma may reflect less treatment received by the uninsured. However, the results are shown to be insensitive to the use of these controls.

effects are included to control for unobservable characteristics that vary by year, such as technological advancement, but affect both the insured and uninsured.

Finally, mortality will be used to test the effect of insurance status on patient outcomes. A linear probability model is used where the dependent variable equals one if the patient died and zero otherwise, which facilitates the use of hospital and year fixed effects.[13]

For person i at hospital h in year t, the estimating equations are:

$$(1) \qquad \ln(Treatment_{iht}) = \gamma_0 + \gamma_1 Uninsured_{iht} + \gamma_2 Personal\,Characteristics_{iht} + \gamma_3 Crash\,Characteristics_{iht} + \theta_h + \delta_t + \varepsilon_{iht} \,,$$

and

$$(2) \qquad Fatal_{iht} = \phi_0 + \phi_1 Uninsured_{iht} + \phi_2 Personal\,Characteristics_{iht} + \phi_3 Crash\,Characteristics_{iht} + \eta_h + \lambda_t + \upsilon_{iht}$$

with the usual exogeneity assumptions: letting Z represent all right hand side variables,

$$(3) \qquad E(\varepsilon_{iht} \mid Z) = E(\upsilon_{iht} \mid Z) = 0$$

The natural log transformation of the treatment variables is standard in the literature, as these variables are right skewed. In addition, given the wide range of ages in the data set, age-squared is included to allow a non-linear relationship.[14] The personal and crash characteristics used as controls are listed in Table 1, with the exception of those with fewer observations. Results are similar in alternative specifications as shown below.

A. The Uninsured Receive Less Treatment

Table 3 presents the main results. Panel A shows the estimates from the treatment regressions. Columns (1) and (5) introduce hospital and year fixed effects, and the uninsured are found to receive fourteen log points fewer charges and twenty log points fewer days in care.

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[13] The results are similar when non-linear models are estimated. In particular, logit and probit models yield similar results to linear probability models that did not include hospital and year fixed effects.

[14] Similar estimates are found when age categories are used as controls.

These estimates are smaller than the insurance effects found in the mean comparisons of Table 1, which showed differences of twenty-nine log points fewer facility charges and twenty-seven log points fewer days in care. This is partly due to the fact that the uninsured tend to be treated at hospitals that offer less treatment to everyone. It could be that the severity of crashes or hospital resources differ in areas where the uninsured live. This implies that it is important to consider the effect of hospital and local area characteristics when measuring treatment differences between the insured and uninsured.[15]

The remaining columns progressively add control variables to demonstrate the stability of the estimates. Columns (2) and (6) include age, sex, and controls for the five major diagnostic categories. While these categories are a function of treatment decisions, inclusion does not change the overall results and serves as an attempt to compare patients with similar types of injury. The main results that include all of the control variables are listed in Columns (3) and (7). Total facility charges are approximately 13 log points lower for the uninsured and length of stay is 16 log points lower. An advantage of the relatively large sample of uninsured patients is that the estimates are fairly precisely estimated with standard errors of approximately 0.02, as shown in Table 3.

Re-transforming the estimates in columns (3) and (7) from log points to percentages, the uninsured are found to receive 20% fewer facility charges and 19% fewer days of care.[16]

[15] The smaller estimates may also be explained by the increased influence of measurement error in models with fixed-effects. However, this explanation is not consistent with the mortality results shown below.

[16] The natural logarithm of each treatment measure is used, as is standard in the health literature where the measures, such as length of stay in the hospital, are right skewed. When interpreting the estimates in terms of percentages or dollars, as opposed to log points or log dollars, the results are re-transformed, and it is necessary to consider heteroskedasticity (Manning, 1998). Consider that the estimating equation is: $\ln \mathrm{T} = \mathrm{X}\beta + \varepsilon \text{ or } T = \exp(X\beta)\exp(\varepsilon)$ and $E(T \mid X) = \exp(X\beta)E(\exp(\varepsilon))$. To compare the two groups, let β_1 be the coefficient associated with being uninsured and evaluate the expectations at common levels of the remaining right-hand-side variables, $\overline{X}_{-1}$ with associated coefficients β_{-1}. The ratio of expected treatment for the two groups is given by:

Evaluated at the sample mean of the control variables, this represents a difference of $3,100 in facility charges and 1.5 days in care.[17]

Columns (4) and (8) introduce a categorical variable equal to one if the primary payer were a Health Maintenance Organization (HMO), with fee-for-service insurance as the omitted category. HMOs are associated with slightly less treatment, three log points fewer days in care and five log points fewer charges. The small difference is not surprising, as fee-for-service plans also contract with hospitals to monitor the care provided. Interestingly, Medicare often pays HMOs five percent less than fee-for-service arrangements—a difference in treatment similar to the one found here.

Other variables largely have the expected results as shown in the appendix. Older and rural patients receive more treatment, as do those who were in a head-on collision, suffered multiple significant trauma, or were trapped in their vehicle. Using a seatbelt or child safety seat is associated with less treatment, as expected from previous studies showing the importance of seatbelts in preventing injury. Vehicle type shows little difference. Finally, women tend to receive slightly less treatment as measured by facility charges, though they stay in care slightly longer.

Differences in Procedures

$$\frac{E(T \mid Uninsured, \bar{X}_{-1})}{E(T \mid Insured, \bar{X}_{-1})} = \exp(\beta_1) * \frac{\exp(\bar{X}_{-1}\beta_{-1})}{\exp(\bar{X}_{-1}\beta_{-1})} * \frac{E(\exp(\varepsilon) \mid Uninsured)}{E(\exp(\varepsilon) \mid Insured)} = \exp(\beta_1) * \frac{E(\exp(\varepsilon) \mid Uninsured)}{E(\exp(\varepsilon) \mid Insured)}$$

Note that because the remaining right hand side variables are evaluated at the same level, they cancel in the ratio. Also, by Jensen's inequality, the expectation of the exponentiated error is greater than the exponential of the expectation of the error. So both groups may have an error term with an expected value of zero, but that need not translate into the exponentiated error terms having the expected value of one. In practice, the expectations can be substituted by their sample counterparts--the average of the exponentiated residuals for the two groups--to form the nonparametric "smearing factor". The re-transformed estimate of the treatment gap is in percentage terms instead of β_1, which is in log points.

[17] In forming the nonparametric "smearing factor", the average exponentiated residuals in the charges regression are 1.46 for the uninsured and 1.61 for the insured. For length of stay, they are 1.37 and 1.43. The predicted values of the retransformed charges and length of stay for the insured are $15,277 and 8.0 days, evaluated at the sample mean of the control variables.

Analyzing individual procedures suggests that the uninsured received less treatment on a broad array of care. Considering the 239 three-digit procedure codes used in these trauma cases, twenty-one procedures were found to differ between the insured and uninsured (at a five-percent level of significance), controlling for crash and personal characteristics. Of those twenty-one, only alcohol rehabilitation was greater among the uninsured. The uninsured received fewer spinal fusions and operations on the brain, kidney, and bladder. They also received fewer amputations, and tracheotomies. This suggests that a lack of health insurance has had a significant effect on treatment decisions on a wide range of health problems, including potentially life saving procedures.

B. Effect on Mortality

Panel B of Table 3 shows the mortality results. Column (1) shows that the uninsured are associated with a 1.3 percentage point increase in mortality when only hospital and year fixed effects are included. This result is stable to the addition of control variables as shown in columns (2)-(4). Column (3) shows that the uninsured have higher mortality by 1.4 percentage points—thirty-seven percent higher than the sample mortality rate of 3.8%. Finally, HMOs and fee-for-service insurance plans have similar mortality rates, which is not surprising given the small difference in treatment between HMOs and fee-for-service insurance plans.

Other variables again have expected effects as shown in the appendix. For example, wearing a seatbelt reduces the risk of death, while an increased risk of death is associated with suffering multiple significant trauma or being trapped in a vehicle.

The use of hospital fixed effects strengthens the mortality result slightly. In models without fixed effects but with all other controls, the coefficient on being uninsured is 0.011 with standard error of 0.005.[18] This is partly due to the fact that the uninsured tend to have greater mortality differences in hospitals that serve fewer uninsured patients. These hospitals may face smaller subsidies for providing charity care to the uninsured, possibly resulting in less care and higher mortality. Again, it is important to consider hospital differences when comparing the insured and uninsured.[19]

5. Specification and Robustness Tests

Provider sensitivity to insurance status has been offered as an explanation for the lower treatment levels and higher mortality rates among the uninsured. However, a number of unobserved characteristics may explain the results. This section presents specification and robustness tests, and the results suggest that unobserved heterogeneity in injuries, crash types, and personal characteristics do not drive the treatment and mortality differences.

No Health Insurance vs. No Automobile Insurance

The mean comparisons in Table 1 show that the uninsured tend to be riskier drivers and drive older, potentially less safe, cars. In addition, we know that the uninsured tend to have less income than the privately insured. These differences suggest that the uninsured may have worse health problems in ways that are difficult to control.

One way to test the effect of these unobserved differences is to compare the uninsured with a similar group of patients. The linked police data provide a novel comparison group: drivers who have health insurance but do not have *automobile* insurance. These drivers have revealed that they take more risks by forgoing insurance. In addition, Table 4 shows that they

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[18] The larger estimates with hospital fixed effects argue against the increased influence of measurement error as an explanation for the smaller treatment differences found when hospital fixed effects were introduced.

[19] Nearly all hospitals in Wisconsin at this time were non-profit organizations, precluding an analysis of the effect of hospital ownership status (public, for-profit, non-profit) on treatment.

are similar to the medically uninsured. They tend to be young (30 vs. 31) and male (76 vs. 72%), drive older cars (9.3 vs. 8.5 years old), and seldom wear a seatbelt. In fact, patients who do not have auto insurance are less likely to wear a seatbelt (14% vs. 23%). They also have similar areas of injury with 17% of those without automobile insurance suffering from multiple significant trauma compared with 15% for drivers without health insurance. In this driver subset, two additional variables are also similar between the groups: an indicator for driving under the influence of alcohol (38% vs. 42%), and an indicator that the driver was at least partially at fault (73% vs. 78%).

The two groups also come from similar neighborhoods. Table 5 reports 1990 US census data comparing ZIP code characteristics where the patients reside. While the neighborhoods where the medically uninsured live differ from those with private health insurance, those with health insurance but no automobile insurance come from similar neighborhoods in terms of race, and education. The income difference is smaller as well.

Finally, there are some differences between the two groups. Those without auto insurance tend to come from larger cities and are more likely to ride a motorcycle. However, results are similar when non-motorcycle drivers are considered.

Table 6 shows the results of regressions similar to Table 3. Rows (1)-(3) show that when comparing medically uninsured drivers with those who have health insurance but do not have automobile insurance, the treatment and mortality differences are similar to those previously found—seventeen log points fewer charges, twenty-one log points fewer days in care, and a 1.9 percentage point higher mortality rate. For comparability purposes, rows (4)-(6) repeat the regressions of Table 3, but for the driver subset and with the additional controls for alcohol use, fault, and automobile insurance status.[20] Again, similar estimates are found.

The next set of results in Table 6 considers patients who have private health insurance and tests whether automobile insurance status affects treatment and mortality. If having no insurance were a proxy for some other cause of the treatment and mortality differences, then the automobile insurance indicator should predict some difference in treatment and mortality. However, Table 6 shows that automobile insurance is not related to treatment or mortality, suggesting that the ability-to-pay of patients is driving the earlier results—not risk preference or income differences between the medically insured and uninsured.[21]

Accident-level fixed effects

Another consideration is that the uninsured may get into crashes that are different in ways that are not controlled in the above regressions. For example, the uninsured may be more likely to crash far from a hospital and the longer travel time may explain the mortality result.[22] However, Table 7 reports results for the 125 accidents where at least one uninsured and one insured patient were deemed incapacitated and visited the same hospital.[23] The treatment and mortality regressions were estimated with accident specific fixed-effects. The results are

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[20] The inclusion of an indicator of automobile insurance does not change the estimates. Also, a model with the full sample that included an indicator if the driver of the vehicle was driving under the influence of alcohol yielded similar estimates.

[21] Analysis was also conducted considering only those who do not have automobile insurance—a smaller sample of 1233 patients of which 375 are uninsured. The medically uninsured and insured are similar in terms of seat belt use and areas of injury, while the uninsured still tend to come from smaller cities and are less likely to ride a motorcycle. Similar results are found with the medically uninsured receiving 21 log points fewer charges with a standard error of 0.059 and 24 log points fewer days in care with a standard error of 0.053. They also have a mortality rate that is 0.095 percentage points higher (standard error 0.009)—again a large difference given the sample average of 1.9 percent, though it is less precisely estimated given the smaller sample size.

[22] Time to the hospital is not available in the data. However, introducing county-of-accident fixed effects to control for cross-county admissions has no effect on the coefficients.

[23] Another 85 accidents occurred with incapacitated insured and uninsured occupants who were delivered to different hospitals. This may be explained by the goal to spread the workload across emergency rooms. Although it is still possible that the uninsured are disproportionately sent to public hospitals, the comparison done here exploits within-hospital variation in an attempt to control for hospital policies and resources, as well as local-area effects.

remarkably similar to the estimates using the larger sample, with 11 log points fewer charges, 16 log points fewer days in care, and a 1.3 percentage point higher mortality rate. Of course, these estimates are measured with less precision due to the smaller sample sizes, but the similarity in the point estimates supports the robustness of the results.

Comparison of Injury Severity

Further results shown in Table 7 suggest that unobserved differences in injury severity do not drive the treatment and mortality results. First, insurance status does not predict police-reported injury severity. Using the full sample of survivors, a linear probability model was estimated with the dependent variable equal to one if police report that the patient were incapacitated and zero otherwise. The full set of controls and hospital and year fixed effects are also included. Table 7 shows that being uninsured is not associated with incapacitation at the scene. Another test focuses on the use of an ambulance. If the uninsured were more likely to refuse to travel by ambulance and arrive later to the hospital, they may be lost from the sample or have systematically different injuries. However, Table 7 shows that insurance status does not predict whether the patient uses an ambulance.

These tests suggest that the uninsured are not likely to have different levels of injury severity. This is also suggested by the finding that the uninsured receive less treatment but have worse health outcomes. For example, the mortality difference may be due to more severe injuries suffered by the uninsured, as suggested by their disproportionate representation in the incapacitation sample, their apparent risk taking behavior of not wearing a seatbelt, and their older, potentially less safe, cars. However, if they had more severe injuries, more treatment should have been observed for survivors, not less. Alternatively, less severe injuries, suggested by the smaller proportion of uninsured patients who were trapped at the accident or who suffered multiple significant trauma, would be associated with less treatment and lower mortality—not higher mortality as observed. While less treatment and higher mortality may be expected if the uninsured were more likely to be almost dead on arrival, estimates below suggest that these cases have little effect on the estimates. The combination of less treatment and higher mortality suggests that the results are not due to systematic differences in injury severity.

Passengers Only

While severity may be similar, uninsured drivers may have some control over whether they are in an accident. This would explain the treatment differences if the uninsured succeeded in avoiding the most severe accidents, while it would explain the mortality result if they had more severe accidents. One way to abstract from the effect of driving quality is to examine passengers only. While uninsured passengers may be similar to drivers, they have less control over the likelihood of an accident. Table 7 shows that the results are similar for the subset of passengers.

Medicaid Recipients vs. the Uninsured

Like those who do not have auto insurance, Medicaid recipients offer another interesting contrast to the uninsured. Medicaid is health insurance publicly provided to those who meet specific criteria such as members of low-income, single-parent families and disabled Supplemental Security Income recipients. If income differences were driving the earlier results, then treatment and outcomes for the uninsured should be similar to Medicaid recipients.

The groups have some major differences, however. The average age for Medicaid recipients in the data is eighteen due to eligibility requirements favoring the inclusion of children, while the average age of the uninsured is twenty-nine. For a better comparison to the earlier results, this section analyzes adults, though the results are not sensitive to this restriction.

Table 5 documents that the neighborhoods where Medicaid recipients live are much different than the other groups, with lower incomes as expected. The neighborhoods also have residents who are less educated and more likely to be black (20% vs. 5%).

Differences between the groups are evident in the patient data as shown in Table 8. Due to eligibility requirements, Medicaid recipients are more likely to be women (58% vs. 27%) though the pattern of results is similar when men and women are analyzed separately. Also, Medicaid recipients are more likely to crash in a large population area (26% vs. 7%). In addition, given that Medicaid eligibility requires a low income or a disability, this group may have worse underlying health status than the uninsured.

Adult Medicaid recipients and the uninsured have some similar observable characteristics. For instance, both groups drive older cars with Medicaid recipients having cars that are 9.4 years old compared to 8.4 years old for the uninsured. In addition, the proportion of Medicaid recipients who wear a seat belt—18%—is the same as the uninsured. The major diagnostic categories are also similar.

Table 9 shows results for treatment and mortality. The effects are magnified, suggesting that income differences between the insured and uninsured are not driving the earlier results. The uninsured receive substantially less treatment (43 log points fewer charges and 52 log points fewer days in care), and have even higher mortality (by 3.4 percentage points). Retransforming the estimates to percentage terms, the uninsured are found to receive forty-nine and fifty percent fewer facility charges and shorter lengths of stay, respectively. As a result, the difference in facility charges is estimated to be $10,200 at the sample mean of the control variables.[24]

[24] When re-transforming the estimates, the average exponentiated residuals in the charges regression are 1.42 for the uninsured and 1.81 for the insured. For length of stay, they are 1.33 and 1.59. The predicted values of the retransformed charges and length of stay for the insured are $20,826 and 11.6 days, evaluated at the sample mean of the control variables.

While the combination of lower treatment levels and higher mortality for the uninsured provides additional support for the earlier results, the difference in treatment is much larger. A likely explanation is that differences in the Medicaid population make comparisons difficult. Medicaid recipients are likely to have poorer underlying health status due to disability eligibility and the effects of poverty. They may become incapacitated more easily and require more treatment due to their previous health problems, despite less severe injuries in the crash. This would partly explain the larger treatment and mortality differences. Accordingly, male Medicaid recipients, who are almost always eligible due to disability requirements, have substantially higher charges compared to women, many of whom qualify due to income standards. Also, treatment differences for children, who usually qualify for Medicaid due to family-income standards, are closer to the differences found between the uninsured and privately insured.

Another explanation for the larger treatment difference is that Wisconsin Medicaid reimbursement rules may encourage greater treatment levels. In Wisconsin, many of the cases studied here qualify for 'outlier' payments—additional funds from Medicaid based on their high cost. That is, additional charges mean additional reimbursement at the margin.[25] In contrast, most private insurers contract with each hospital and pay on a capitated basis—the hospital is paid a fixed amount for each individual treated as an inpatient. These results suggest that Medicaid's cost-based reimbursement scheme may lead to greater treatment levels.

Medicaid benefits in Wisconsin are generous, which may prevent contractors, such as HMOs that manage part of the Wisconsin Medicaid program, from restricting physician choices. Further, Duggan (2000) shows that Medicaid patients were more profitable in California over

[25] When costs exceed reimbursement by $31,000 for large hospitals and $5,100 for small hospitals, Medicaid reimbursement is roughly fifty percent of the hospital charges above the threshold.

this period.[26] This may be true in Wisconsin as well, as Medicaid appears to be more generous there than in California.[27] In addition, Skinner and Silverman (2001), Dafny (2002), among others, show that payments can vary substantially within illness categories. They find evidence that hospitals categorize Medicare patients in diagnostic groups that offer greater payments. Consistent with this notion "upcoding" in the Medicaid program, the introduction of controls for diagnosis-related groups decreases the treatment differences as discussed below.

Finally, the larger treatment differences may be due to more adequately matched samples in terms of unobserved injury severity. If the uninsured suffered from worse injuries in ways that are not controlled, then the magnitude of the estimated treatment differences would be smaller than the true differences. This would imply that the results comparing the uninsured with the privately insured may understate the effect of insurance on treatment, though this would be inconsistent with the mortality differences found.[28] However, this possibility was tested using a propensity score approach (Rosenbaum and Rubin, 1983) for the uninsured versus privately insured comparison, and similar results were found.[29]

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[26] This was done through additional subsidies to hospitals with large shares of low-income patients, paid on a per-diem basis for Medicaid recipients. While Wisconsin did not take as large a part in this Federal program as California did, Wisconsin did begin its own initiative to subsidize the treatment of Medicaid patients in such hospitals.

[27] According to the Health Care Financing Administration (HCFA), Medicaid spending per recipient is nearly twice as large in Wisconsin compared to California (www.hcfa.gov).

[28] Another explanation would be that the most severely-injured, uninsured patients were deemed disabled and therefore eligible for Medicaid. In this case, the remaining uninsured patients would necessarily receive lower treatment levels. However, the expected payer is defined as the person or organization to which the bill was originally submitted. According to Wisconsin hospital administrators, determining Medicaid eligibility usually takes over five months—long after most patients are discharged. As shown below, the comparisons are robust to restricting the sample to stays that were less than one month.

[29] The propensity score is a predicted probability that a given patient is uninsured. Within deciles of these scores, the control variables are similar, or balanced, and it is hoped that the unobserved characteristics are also similar. However, attempts were not made to balance the choice of hospitals between the insured and uninsured given the large number of options (115 hospitals). The treatment differences are found to be larger—similar to the results of models without hospital fixed-effects. Mortality results were noisier given the smaller sample sizes. Seven deciles had insurance effects of greater than one percentage point, of which three had mortality rates greater than two percentage points, and two deciles where the uninsured had a lower mortality rate with magnitudes greater than one half of one percentage point. There was little pattern in the mortality results, suggesting that severity of injury did not systematically increase with the propensity to be uninsured.

Robustness to Sample Changes and Additional Controls

The results are robust across a number of specifications as shown in Table 10. For example, the results are similar for samples including: the entire data set, adults, patients who did not use a seatbelt or safety seat, and all those who traveled by ambulance even if they were not judged by police to be incapacitated. For the ambulance transfer sample, the coefficient on being uninsured in the mortality equation is 0.01. This is again quite large given that the mortality rate in this subset is 2.5%.

To consider patient decisions, the results are robust to dropping observations where the patient left the hospital "against medical advice." This happens in rare cases, though not surprisingly more frequently for the uninsured (1.4% vs. 0.3%). However, Table 10 shows that the results are not sensitive to dropping these observations.

The adequacy of controlling for injury severity is also considered. The results are similar when dummy variables for 285 diagnostic related groups (DRG) are introduced. While including the five major diagnostic categories served to control for the broad area of injury, these groups are more specific. For example, DRGs include "peripheral and cranial nerve and other nerve system procedures" and "major chest trauma without complications or comorbitites". However, the DRG is defined by combinations of procedures and diagnoses that may be related to insurance status. If the uninsured were given less care, they would be compared with insured patients who were less severely injured. This would tend to shrink the treatment differences and widen the mortality differences. While the coefficients move in those directions, the similar results further demonstrate the robustness of the findings.

Table 10 also reports the treatment results in models where the level of treatment is used as the dependent variable, instead of using the natural log transformation. Differences in treatment increase for total facility charges to $3,800, but are similar for length of stay (1.5 days).

If uninsured patients were more likely to be very close to death when entering the hospital, then treatment may be lower for these patients. However, Table 10 shows that removing patients who were given little treatment from the analysis does not alter the results. Trimming the data of observations with both large and small values of treatment does not affect the main results. Similarly, the re-transformed estimates are not affected by trimming.

Finally, Table 10 shows that the Medicaid comparisons are robust as well. However, differences are smaller when children are included and when large values of treatment are dropped. Consistent with upcoding, the use of DRG fixed effects yields smaller treatment differences, but larger mortality differences.

6. Implications

Previous studies found that the uninsured received approximately 40% less health care than the insured, though some estimates are as low as twenty-five percent (Marquis and Long (1994) offer a review, Haas and Goldman (1994) show results for emergency care). The estimates here are at the low end of this range, suggesting that previous estimates of treatment differences may have had substantial selection bias.

While the treatment difference is less than previously found, it is still substantial and represents a relatively low cost of saving a statistical life. The difference in facility charges is estimated to be $3,100 at the sample mean of the control variables.[30] With an increased

[30] Cost audits performed by Medicaid and Medicare suggest that the cost of the treatment is roughly seventy percent of charges, consistent with private insurers typically contracting with hospitals to pay seventy-five to eighty percent of charges. However, items that are excluded from facility charges, such as physician fees, roughly offset this adjustment. Comparing aggregate data for total charges and total facility charges in Wisconsin reveals that total

mortality rate of 1.4 percentage points, the implied cost of saving a statistical life, then, is roughly \$221,000 (=\$3,100/0.014). For the adult Medicaid-uninsured comparison, the implied cost of saving a statistical life increases to \$300,000.

This is much cheaper than most attempts to lower mortality, especially given how young the uninsured are. Tengs et.al. (1995) discuss five hundred life-saving interventions and find that the median cost *per life-year* saved from fatal injury reductions is \$48,000. For other interventions such as toxin control, the estimate increases to \$2.8 million. Given the \$221,000 cost of saving a statistical life attributed to health insurance, the comparable figure here would be approximately \$11,000 per life-year saved.[31]

To place the increased risk of death in context, it is larger than a more commonly considered effect of health provider actions—complications or misadventures during surgery. It is estimated that there is a thirty-percent chance of being in a serious automobile accident in a lifetime.[32] Say the insured and uninsured face that same risk, but the uninsured are more likely to die by 1.4 percentage points. This implies that the uninsured have a 0.42 percentage point increase in the lifetime risk of dying due to severe automobile accidents. This is five times the lifetime risk of dying due to complications or misadventures during surgery.

Taking this calculation one step further, it is possible to place a rough value on having insurance. If the value were much larger than the cost of insurance, then these results may be regarded as "too big." However, it appears that the cost of catastrophic health insurance is

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facility charges are seventy-two percent of total charges. Note that these cost audits reveal that accounting procedures do vary by hospital—one reason why exploiting within-hospital variation is important.

[31] Assuming an equal cost per life-year saved and a discount rate of 5%, the discounted present value of spending \$11,000 each year in perpetuity would be approximately \$221,000—the cost of saving a statistical life calculated above.

[32] The National Safety Council calculates the lifetime risk of death in an automobile accident to be roughly 1.25%. This is roughly consistent with the estimated thirty-percent chance of a severe accident and a 4% chance of death once in a severe accident. The lifetime risk of death due to complications or misadventures during surgery is calculated to be 0.08%.

similar in magnitude to the value of the reduction in mortality. Taking the 0.42 percentage point decrease in lifetime risk, and assuming, for the moment, that each year is an independent and equal risk, then the annual decrease in the risk of death for an insured adult is approximately 0.01 percentage points. Given a value of life estimate of three million dollars, the willingness to pay for a 0.01 percentage point decrease in the annual risk of death would be approximately $300(=$3,000,000*0.0001) per year. In a casual survey of catastrophic insurance rates in Wisconsin, a policy with a $1500 deductible was found to be approximately $300 per year for a twenty-three year old man. It appears, then, that the magnitudes of the benefits and costs of catastrophic insurance are roughly similar and that the differences in treatment and mortality are not unreasonably large.

Flat-of-the-curve Medicine

There is a debate in the health literature over whether diminishing returns have set in on the ability of health care to improve outcomes. Physicians may be practicing 'flat-of-the-curve' medicine, as discussed in section two. However, an empirical test of the effectiveness of additional treatment is complicated by the fact that more severely ill patients receive more health care. For example, Table 2 shows that for patients who die—the most severely injured—total facility charges are greater. More treatment is associated with worse health outcomes.

However, the analysis here suggests that we are not on the "flat-of-the-curve". An alternative characterization of the results is to consider insurance status as an instrumental variable for treatment. If insurance status were related to treatment levels because providers are sensitive to the patient's ability-to-pay, and not due to differences in unobserved injury severity, then insurance status could used as an instrumental variable for treatment. This would break the spurious positive relationship between treatment and mortality. The first stage is represented in

Table 3 where treatment is regressed on insurance status to calculate the predicted facility charges. The second stage, which predicts the probability of death, reveals a coefficient on the instrumented charges of –0.114 with a standard error of 0.047. This implies that a one-percent increase in charges is associated with a reduction in the mortality rate of 0.11 percentage points.[33] Again, this is a large difference as suggested by the low cost per statistical life saved calculated above. It appears that when it comes to emergency medicine, we are not on the "flat of the curve".

If evidence had been found for flat-of-the-curve medicine, then welfare implications would stem from distorted insurance prices. However, with mortality differences, the welfare implications are not straightforward. The uninsured may receive too little care, the insured may receive too much, or both.

7. Conclusion

Using automobile accidents as unexpected health shocks where contact with medical professionals is virtually automatic, this paper avoids selection problems inherent in previous studies. The results suggest that there are real consequences to being uninsured. Controlling for personal, crash, and hospital characteristics, the uninsured are estimated to receive 20% less treatment than the privately insured following serious accidents. In addition, there appear to be large effects on mortality. The uninsured are found to have a 1.4 percentage point higher mortality rate compared with a mean mortality rate of 3.8%. These estimates imply that physicians are not practicing 'flat-of-the-curve' medicine, at least in these trauma cases.

[33] This result can be derived from the above tables: given a difference of 13 log points in charges from the first stage, this represents an increased mortality rate of approximately 1.5 percentage points (–0.114 x –13) similar to the earlier results. When length of stay is instrumented, the increase in mortality is approximately 1.4 percentage points.

These differences appear to be attributable to provider sensitivity toward insurance status, as opposed to unobserved characteristics of the uninsured. For example, similar groups, such as drivers who have health insurance but do not have automobile insurance, receive more treatment and die less. In addition, the uninsured receive fewer major operations—decisions that are likely the domain of physicians. Finally, the combination of less treatment and higher mortality is inconsistent with systematic differences in health status between the insured and uninsured. It appears, then, that having health insurance significantly affects treatment decisions and ultimately patient outcomes.

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Table 1: Summary Statistics for those Incapacitated at the Scene

Variable		Privately Insured Mean	Privately Insured Std Dev	Uninsured Mean	Uninsured Std Dev	t
Treatment	length of stay	9.176	13.914	6.518	8.563	7.43
	ln(length of stay)	1.733	0.904	1.462	0.839	11.24
	facility charges	20.699	37.272	13.392	21.663	7.64
	ln(facility charges)	2.271	1.177	1.979	1.057	9.31
Outcome	fatal	0.037	0.188	0.044	0.205	1.45
Personal Characteristics	age	30.172	14.406	28.840	11.701	3.51
	female	0.377	0.485	0.284	0.451	7.16
Major Diagnostic Categories	nervous system	0.205	0.404	0.214	0.410	0.80
	respiratory	0.069	0.253	0.068	0.251	0.15
	musculoskeletal & tissue	0.351	0.477	0.353	0.478	0.12
	skin, tissue, & breast	0.063	0.243	0.078	0.269	2.27
	multiple significant trauma	0.197	0.398	0.163	0.370	3.16
	other	0.115	0.318	0.124	0.329	1.06
Vehicle Types	car	0.607	0.488	0.602	0.490	0.41
	truck	0.135	0.342	0.131	0.337	0.54
	mcycle	0.140	0.347	0.151	0.358	1.18
	bus	0.001	0.034	0.000	0.000	1.38
	equipment	0.009	0.094	0.009	0.093	0.11
	bike	0.032	0.175	0.030	0.172	0.28
	pedestrian	0.076	0.264	0.078	0.268	0.29
Crash Characteristics	car driver	0.526	0.499	0.493	0.500	2.39
	car passenger	0.227	0.419	0.247	0.432	1.79
	restraint (seat belt/child seat)	0.302	0.459	0.186	0.389	9.56
	severe vehicle damage	0.494	0.500	0.484	0.500	0.78
	trapped	0.172	0.378	0.149	0.356	2.36
	head-on collision	0.127	0.333	0.116	0.320	1.24
	angle collision	0.290	0.454	0.219	0.414	5.92
	sideswipe collision	0.044	0.205	0.050	0.219	1.17
	other collision	0.539	0.498	0.615	0.487	5.68
	wet pavement	0.243	0.429	0.211	0.408	2.78
Road Types	urban street	0.200	0.400	0.222	0.416	2.08
	rural street	0.364	0.481	0.390	0.488	1.95
	urban highway	0.092	0.290	0.083	0.275	1.25
	rural highway	0.297	0.457	0.267	0.442	2.48
	urban interstate	0.014	0.117	0.007	0.086	2.11
	rural interstate	0.032	0.177	0.031	0.174	0.28
Population Size	small town (<25,000)	0.787	0.410	0.766	0.423	1.82
	medium town (<250,000)	0.148	0.355	0.155	0.362	0.69
	large town (>250,000)	0.065	0.247	0.079	0.270	2.01
Fewer Observations	airbag deployed	0.074	0.261	0.040	0.196	4.02
	ejected	0.263	0.440	0.253	0.435	0.64
	posted speed limit	47.573	12.430	46.585	13.002	2.76
	car age	7.242	3.937	8.416	3.982	9.11
	Observations	9353		1609		

The number of observations for airbag deployment and ejected are 7,109; speed limit 9,719; car age 8,111; ln(charges) 10,960.

Table 2: Treatment by Injury Severity and Insurance Status

		Privately Insured				Uninsured			
		Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
Fatal									
	total charges (000's)	27.48	29.68	2.33	170.35	17.44	13.54	1.46	75.84
	length of stay	4.51	5.33	1.00	30.00	2.97	3.80	1.00	20.00
	Observations	336				67			
Incapacitating Injury									
	total charges (000's)	20.45	37.50	0.00	974.41	13.22	21.93	0.29	369.27
	length of stay	9.35	14.10	1.00	355.00	6.67	8.68	1.00	94.00
	Observations	9017				1542			
Non-incapacitating Injury									
	total charges (000's)	7.50	12.68	0.26	282.40	6.55	12.33	0.41	233.94
	length of stay	4.75	5.62	1.00	89.00	3.89	4.33	1.00	64.00
	Observations	3585				671			
Possible Injury									
	total charges (000's)	6.43	12.31	0.26	260.49	4.36	5.74	0.27	45.56
	length of stay	4.46	5.88	1.00	143.00	3.23	3.04	1.00	23.00
	Observations	1375				212			

Table 3: The Uninsured Receive Less Treatment than the Privately Insured

A. Treatment

	Ln(Total Charges)				Ln(Length of Stay)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
uninsured	-0.140	-0.128	-0.127	-0.136	-0.195	-0.167	-0.163	-0.176
	(0.026)	(0.024)	(0.024)	(0.026)	(0.023)	(0.022)	(0.022)	(0.023)
HMO				-0.046				-0.030
				(0.026)				(0.022)
Major Diagnostic Categories and Personal Characteristics Included	No	Yes	Yes	Yes	No	Yes	Yes	Yes
All Controls Included	No	No	Yes	Yes	No	No	Yes	Yes
Observations	10960	10960	10960	9969	10962	10962	10962	9971
R-squared	0.25	0.37	0.38	0.38	0.12	0.21	0.22	0.22

B. Outcome

	Mortality			
	(1)	(2)	(3)	(4)
uninsured	0.013	0.015	0.014	0.016
	(0.006)	(0.006)	(0.006)	(0.006)
HMO				-0.002
				(0.005)
Major Diagnostic Categories and Personal Characteristics Included	No	Yes	Yes	Yes
All Controls Included	No	No	Yes	Yes
Observations	10962	10962	10962	9971
R-squared	0.03	0.06	0.07	0.07

Models include hospital and year fixed effects; Robust standard errors in parentheses.

Table 4: Summary Statistics: Drivers with No Auto Insurance vs. No Health Insurance

		Private Health Insurance But No Automobile Insurance		No Health Insurance		t
Variable		**Mean**	**Std Dev**	**Mean**	**Std Dev**	
Treatment	length of stay	8.695	10.513	6.438	7.668	4.836
	ln(length of stay)	1.733	0.881	1.472	0.833	6.053
	facility charges	19.900	31.604	13.912	21.975	4.328
	ln(facility charges)	2.303	1.126	2.008	1.068	5.352
Outcome	fatal	0.017	0.129	0.033	0.179	2.092
Personal Characteristics	age	30.380	10.852	30.765	10.601	0.719
	female	0.238	0.426	0.278	0.449	1.874
Major Diagnostic Categories	nervous system	0.184	0.387	0.188	0.391	0.225
	respiratory	0.056	0.231	0.062	0.241	0.461
	musculoskeletal & tissue	0.393	0.489	0.380	0.486	0.536
	skin, tissue, & breast	0.062	0.241	0.081	0.273	1.485
	multiple significant trauma	0.166	0.372	0.150	0.357	0.878
	other	0.140	0.347	0.140	0.347	0.016
Vehicle Types	car	0.489	0.500	0.636	0.481	6.012
	truck	0.098	0.297	0.133	0.340	2.213
	mcycle	0.413	0.493	0.230	0.421	7.920
	other	n/a	n/a	n/a	n/a	n/a
Crash Characteristics	restraint (seat belt/child seat)	0.144	0.351	0.232	0.422	4.557
	severe vehicle damage	0.413	0.493	0.524	0.500	4.467
	trapped	0.120	0.326	0.173	0.378	2.989
	head-on collision	0.108	0.311	0.152	0.360	2.648
	angle collision	0.255	0.436	0.224	0.417	1.447
	sideswipe collision	0.043	0.203	0.064	0.246	1.945
	other collision	0.595	0.491	0.560	0.497	1.415
	wet pavement	0.166	0.372	0.217	0.412	2.622
Road Types	urban street	0.231	0.422	0.170	0.376	3.027
	rural street	0.384	0.487	0.414	0.493	1.237
	urban highway	0.114	0.318	0.089	0.285	1.620
	rural highway	0.239	0.427	0.296	0.457	2.614
	urban interstate	0.014	0.116	0.005	0.074	1.623
	rural interstate	0.019	0.137	0.025	0.155	0.762
Population Size	small town (<25,000)	0.727	0.446	0.819	0.385	4.362
	medium town (<250,000)	0.175	0.380	0.128	0.334	2.612
	large town (>250,000)	0.098	0.297	0.053	0.225	3.329
Additional Driver Variables	DUI	0.384	0.487	0.417	0.493	1.348
	At Fault	0.730	0.444	0.776	0.417	2.161
Fewer Observations	airbag deployed	0.024	0.153	0.056	0.231	2.601
	ejected	0.438	0.497	0.269	0.444	5.630
	posted speed limit	44.143	12.905	46.685	12.420	3.931
	car age	9.303	3.852	8.475	4.070	3.539
	Observations	888		729		

The total number of observations for airbag deployment and ejected are 982; speed limit 1553; car age 1146.

Table 5: ZIP code Comparisons

ZIP code Characteristics	Uninsured	Privately Insured	No Auto Insurance	Medicaid
Black	0.047	0.032*	0.055	0.20**
White	0.92	0.95**	0.92	0.75**
No High School	0.11	0.099**	0.10*	0.11
Some High School	0.13	0.12**	0.13	0.17**
High School	0.38	0.38	0.38	0.35**
Some College	0.22	0.23**	0.23**	0.23*
Median Household Income	27643	30410**	28766**	24740**
Observations	1476	8633	1200	1050

488 ZIP codes

*=significant difference from 'uninsured' at the 5% level, with ZIP-clustered standard errors;

**=significant difference from 'uninsured' at the 1% level, with ZIP-clustered standard errors;

Educational Attainment is for Adults > 25 years old.

Source: 1990 US Census

Table 6: No Automobile Insurance vs. No Health Insurance

Sample	Dependent Variable	Uninsured Coeff.	Std. Error	Observations
Uninsured=No Health Insurance				
Drivers with no health insurance vs. drivers with private health insurance but no auto insurance	Ln(charges)	-0.166	(0.049)	1617
	Ln(length of stay)	-0.206	(0.043)	1617
	Mortality	0.019	(0.009)	1617
Drivers	Ln(charges)	-0.136	(0.037)	5973
	Ln(length of stay)	-0.162	(0.033)	5974
	Mortality	0.015	(0.007)	5974
Uninsured=No Auto Insurance				
Drivers with private health insurance	Ln(charges)	-0.007	(0.035)	5320
	Ln(length of stay)	-0.003	(0.030)	5321
	Mortality	-0.005	(0.005)	5321

Models include full controls and hospital and year fixed effects; Robust standard errors in parentheses.

Table 7: Additional Tests

		Uninsured Coeff.	Std. Error	Observations
Accident Fixed Effects				
	Ln(charges)	-0.114	(0.111)	255
	Ln(length of stay)	-0.155	(0.104)	255
	Mortality	.0130	(0.024)	255
Incapacitation				
All Survivors	Incapacitated	-0.003	(0.010)	17388
All	Go in Ambulance	-0.001	(0.007)	18901
Car Passengers	Ln(charges)	-0.166	(0.053)	2388
	Ln(length of stay)	-0.228	(0.048)	2389
	Mortality	0.015	(0.012)	2389

All models include full controls and hospital and year fixed effects. Robust standard errors are reported.

Table 8: Summary Statistics for the Uninsured and Medicaid Recipients over the age of 17

Variable		Medicaid Mean	Medicaid Std Dev	Uninsured Mean	Uninsured Std Dev	t
Treatment	length of stay	14.75	24.74	6.58	8.56	10.97
	ln(length of stay)	1.98	1.10	1.47	0.84	11.16
	facility charges	34.02	64.42	13.59	21.81	10.58
	ln(facility charges)	2.48	1.41	1.99	1.06	8.51
Outcome	fatal	0.02	0.15	0.04	0.20	1.89
Personal Characteristics	age	32.51	10.97	30.96	10.60	2.94
	female	0.58	0.49	0.27	0.44	13.99
Major Diagnostic Categories	nervous system	0.22	0.41	0.20	0.40	0.60
	respiratory	0.05	0.23	0.07	0.26	1.57
	musculoskeletal & tissue	0.36	0.48	0.36	0.48	0.07
	skin, tissue, & breast	0.07	0.25	0.08	0.27	1.09
	multiple significant trauma	0.16	0.37	0.16	0.37	0.20
	other	0.14	0.35	0.12	0.33	1.00
Vehicle Types	car	0.70	0.46	0.61	0.49	4.08
	truck	0.06	0.24	0.14	0.34	4.66
	mcycle	0.08	0.26	0.17	0.37	5.40
	bus	0.00	0.00	0.00	0.00	.
	equipment	0.00	0.00	0.01	0.08	2.03
	bike	0.01	0.12	0.02	0.15	1.18
	pedestrian	0.14	0.35	0.06	0.24	6.10
Crash Characteristics	car driver	0.48	0.50	0.54	0.50	2.18
	car passenger	0.28	0.45	0.21	0.41	3.37
	restraint (seat belt/child seat)	0.18	0.38	0.18	0.39	0.23
	severe vehicle damage	0.42	0.49	0.49	0.50	2.86
	trapped	0.15	0.35	0.15	0.36	0.49
	head-on collision	0.09	0.28	0.12	0.32	2.07
	angle collision	0.29	0.45	0.20	0.40	4.00
	sideswipe collision	0.05	0.21	0.05	0.22	0.59
	other collision	0.58	0.49	0.62	0.48	1.84
	wet pavement	0.22	0.41	0.21	0.41	0.33
Road Types	urban street	0.36	0.48	0.21	0.41	6.77
	rural street	0.28	0.45	0.39	0.49	4.58
	urban highway	0.11	0.32	0.08	0.28	2.26
	rural highway	0.22	0.41	0.27	0.45	2.68
	urban interstate	0.01	0.08	0.01	0.08	0.14
	rural interstate	0.02	0.15	0.03	0.18	1.28
Population Size	small town (<25,000)	0.60	0.49	0.77	0.42	7.94
	medium town (<250,000)	0.14	0.35	0.15	0.36	0.78
	large town (>250,000)	0.26	0.44	0.07	0.26	11.78
Fewer Observations	airbag deployed	0.02	0.13	0.05	0.21	2.35
	ejected	0.20	0.40	0.27	0.44	2.57
	posted speed limit	43.89	13.27	46.63	12.94	3.92
	car age	9.36	3.35	8.41	4.02	3.94
	Observations	583		1425		

The number of observations for Airbag and Ejected are 1,300; Speed Limit 1,771; Car Age 1,328.

Table 9: Adult Uninsured Receive Less Treatment than Adult Medicaid Recipients

A. Treatment

	Ln(Total Charges)				Ln(Length of Stay)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
uninsured	-0.344	-0.407	-0.431	-0.436	-0.477	-0.505	-0.520	-0.526
	(0.059)	(0.057)	(0.057)	(0.060)	(0.051)	(0.051)	(0.051)	(0.053)
Medicaid hmo				-0.067				0.000
				(0.130)				(0.117)
Major Diagnostic Categories and Personal Characteristics Included	No	Yes	Yes	Yes	No	Yes	Yes	Yes
All Controls Included	No	No	Yes	Yes	No	No	Yes	Yes
Observations	2008	2008	2008	1997	2008	2008	2008	1997
R-squared	0.33	0.43	0.46	0.46	0.22	0.30	0.32	0.32

B. Outcome

	Mortality			
	(1)	(2)	(3)	(4)
uninsured	0.030	0.034	0.034	0.031
	(0.010)	(0.010)	(0.011)	(0.011)
Medicaid HMO				-0.022
				(0.023)
Major Diagnostic Categories and Personal Characteristics Included	No	Yes	Yes	Yes
All Controls Included	No	No	Yes	Yes
Observations	2008	2008	2008	1997
R-squared	0.07	0.10	0.12	0.12

Models include hospital and year fixed effects; Robust standard errors in parentheses.

Table 10: Robustness to Sample Changes and Additional Controls

Uninsured vs Private Insurance

	Ln (Charges)		**Ln (Length of Stay)**		**Mortality**		
	Uninsured Coeff.	Std Error	Uninsured Coeff.	Std Error	Uninsured Coeff.	Std Error	Observations
All Data	-0.110	(0.018)	-0.166	(0.015)	0.012	(0.003)	26810
All Ages No Age Squared	-0.124	(0.024)	-0.170	(0.022)	0.011	(0.005)	11967
All Ages	-0.122	(0.024)	-0.162	(0.022)	0.014	(0.006)	11967
Adults	-0.133	(0.026)	-0.152	(0.024)	0.012	(0.006)	8799
Ambulance Transfer	-0.115	(.020)	-0.151	(0.017)	0.010	(0.004)	15622
No Seatbelt	-0.134	(0.027)	-0.167	(0.025)	0.015	(0.006)	7804
Trim: Top 1% of Charges	-0.135	(0.023)	-0.170	(0.021)	0.014	(0.006)	10851
Trim: Top 1% of Length of Stay	-0.135	(0.023)	-0.171	(0.021)	0.014	(0.006)	10847
Length of Stay<30 days	-0.098	(0.023)	-0.138	(0.020)	0.013	(0.006)	10467
Charge>$1,000	-0.130	(0.024)	-0.162	(0.022)	0.014	(0.006)	10808
>1 Procedure or >1 One Day	-0.113	(0.024)	-0.144	(0.022)	0.014	(0.006)	10725
No Leave Against Med. Advice	-0.123	(0.025)	-0.158	(0.022)	0.014	(0.006)	10916
DRG Fixed Effects	-0.084	(0.018)	-0.134	(0.019)	0.017	(0.005)	10784
Levels: Charges ('000s), LOS (days)	-3.811	(0.652)	-1.461	(0.265)			10962

Adult Uninsured vs Adult Medicaid

	Ln (Charges)		**Ln (Length of Stay)**		**Mortality**		
	Uninsured Coeff.	Std Error	Uninsured Coeff.	Std Error	Uninsured Coeff.	Std Error	
All Aged<65	-0.345	(0.047)	-0.464	(0.042)	0.043	(0.009)	2708
Trim: Top 1% of Charges	-0.431	(0.056)	-0.519	(0.050)	0.034	(0.011)	1987
Trim: Top 1% of Length of Stay	-0.426	(0.056)	-0.517	(0.049)	0.034	(0.011)	1986
Length of Stay<30 days	-0.210	(0.051)	-0.306	(0.043)	0.028	(0.011)	1905
DRG Fixed Effects	-0.204	(0.040)	-0.352	(0.043)	0.044	(0.011)	1989

Models include full controls and hospital and year fixed effects; Robust standard errors in parentheses.

Table A1: Full Treatment Results

	Ln(Total Charges)				Ln(Length of Stay)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
uninsured	-0.140	-0.128	-0.127	-0.136	-0.195	-0.167	-0.163	-0.176
	(0.026)	(0.024)	(0.024)	(0.026)	(0.023)	(0.022)	(0.022)	(0.023)
private hmo				-0.046				-0.030
				(0.026)				(0.022)
nervous system injury		0.130	0.120	0.082		0.203	0.195	0.164
		(0.038)	(0.038)	(0.039)		(0.031)	(0.030)	(0.032)
respiratory injury		0.012	0.018	-0.010		0.191	0.191	0.171
		(0.044)	(0.043)	(0.045)		(0.034)	(0.034)	(0.035)
musculoskeletal & tissue injury		0.202	0.184	0.153		0.275	0.258	0.229
		(0.031)	(0.031)	(0.033)		(0.025)	(0.025)	(0.026)
skin, tissue, breast injury		-0.452	-0.451	-0.494		-0.293	-0.294	-0.335
		(0.038)	(0.038)	(0.040)		(0.031)	(0.030)	(0.032)
multiple significant injury		1.028	0.980	0.937		0.735	0.704	0.672
		(0.034)	(0.034)	(0.035)		(0.030)	(0.030)	(0.032)
age		0.014	0.011	0.011		0.001	0.000	0.001
		(0.003)	(0.003)	(0.003)		(0.003)	(0.003)	(0.003)
age squared		-0.137	-0.083	-0.088		0.057	0.073	0.055
		(0.043)	(0.043)	(0.045)		(0.038)	(0.039)	(0.040)
female		-0.082	-0.048	-0.041		0.024	0.045	0.051
		(0.019)	(0.020)	(0.020)		(0.016)	(0.017)	(0.018)
driver			-0.172	-0.072			-0.012	-0.300
			(0.313)	(0.107)			(0.083)	(0.195)
passenger			-0.157	-0.049			0.008	-0.272
			(0.312)	(0.109)			(0.085)	(0.195)
restraint			-0.163	-0.151			-0.084	-0.068
			(0.022)	(0.023)			(0.019)	(0.020)
severe damage			0.063	0.078			0.023	0.031
			(0.029)	(0.030)			(0.025)	(0.026)
trapped			0.220	0.216			0.116	0.114
			(0.027)	(0.028)			(0.024)	(0.025)
wet pavement			0.006	0.011			0.013	0.016
			(0.022)	(0.023)			(0.019)	(0.020)
angle collision			-0.268	-0.271			-0.136	-0.139
			(0.031)	(0.032)			(0.027)	(0.028)
sideswipe collision			-0.103	-0.088			-0.058	-0.057
			(0.049)	(0.052)			(0.042)	(0.044)
other collision			-0.193	-0.193			-0.122	-0.127
			(0.029)	(0.030)			(0.025)	(0.027)
car			0.044	-0.084			-0.101	0.155
			(0.312)	(0.106)			(0.083)	(0.193)
truck			0.069	-0.039			-0.078	0.207
			(0.312)	(0.108)			(0.085)	(0.194)
rural street			0.198	0.205			0.104	0.118
			(0.039)	(0.040)			(0.034)	(0.034)
urban highway			-0.002	0.001			0.001	0.011
			(0.037)	(0.038)			(0.031)	(0.032)
rural highway			0.194	0.193			0.106	0.112
			(0.040)	(0.041)			(0.034)	(0.035)
urban interstate			0.065	0.069			0.025	0.032
			(0.084)	(0.084)			(0.068)	(0.068)
rural interstate			0.150	0.146			0.059	0.057
			(0.064)	(0.067)			(0.055)	(0.057)
small town			0.168	0.163			0.137	0.130
			(0.057)	(0.058)			(0.049)	(0.050)
medium town			0.162	0.173			0.097	0.105
			(0.055)	(0.056)			(0.048)	(0.049)
Constant	2.412	1.873	1.677	1.728	1.709	1.347	1.318	1.417
	(0.025)	(0.058)	(0.083)	(0.087)	(0.022)	(0.051)	(0.074)	(0.075)
Observations	10960	10960	10960	9969	10962	10962	10962	9971
R-squared	0.25	0.37	0.38	0.38	0.12	0.21	0.22	0.22

Models include hospital and year fixed effects; Robust standard errors in parentheses; Other vehicle types not shown;
Omitted categories are head-on collision, motorcycle, bicycle & pedestrians, urban street, & large town.

Table A2: Full Mortality Results

	Mortality			
	(1)	(2)	(3)	(4)
uninsured	**0.013**	**0.015**	**0.014**	**0.016**
	(0.006)	(0.006)	(0.006)	(0.006)
HMO				**-0.002**
				(0.005)
nervous system injury		**0.029**	**0.028**	**0.028**
		(0.006)	(0.006)	(0.007)
respiratory injury		**-0.008**	**-0.008**	**-0.008**
		(0.006)	(0.006)	(0.007)
musculoskeletal & tissue injury		**-0.020**	**-0.022**	**-0.022**
		(0.004)	(0.004)	(0.005)
skin, tissue, breast injury		**-0.019**	**-0.021**	**-0.021**
		(0.004)	(0.004)	(0.005)
multiple significant injury		**0.077**	**0.075**	**0.074**
		(0.008)	(0.008)	(0.008)
age		**-0.001**	**-0.001**	**-0.002**
		(0.001)	(0.001)	(0.001)
age squared (000's)		**0.023**	**0.026**	**0.028**
		(0.009)	(0.009)	(0.010)
female		**-0.001**	**0.002**	**0.001**
		(0.004)	(0.004)	(0.004)
driver			**-0.009**	**-0.019**
			(0.017)	(0.011)
passenger			**-0.012**	**-0.022**
			(0.018)	(0.011)
restraint			**-0.008**	**-0.007**
			(0.004)	(0.005)
severe damage			**0.004**	**0.003**
			(0.006)	(0.006)
trapped			**0.013**	**0.013**
			(0.006)	(0.006)
wet pavement			**0.007**	**0.009**
			(0.004)	(0.005)
angle collision			**0.005**	**0.005**
			(0.006)	(0.006)
sideswipe collision			**0.012**	**0.012**
			(0.010)	(0.010)
other collision			**0.009**	**0.009**
			(0.005)	(0.006)
car			**0.001**	**0.012**
			(0.017)	(0.010)
truck			**0.002**	**0.009**
			(0.018)	(0.011)
rural street			**0.010**	**0.012**
			(0.007)	(0.008)
urban highway			**0.014**	**0.012**
			(0.008)	(0.008)
rural highway			**0.008**	**0.007**
			(0.007)	(0.008)
urban interstate			**-0.013**	**-0.013**
			(0.015)	(0.015)
rural interstate			**0.018**	**0.020**
			(0.013)	(0.013)
small town			**-0.018**	**-0.018**
			(0.012)	(0.012)
medium town			**-0.012**	**-0.009**
			(0.012)	(0.012)
Constant	**0.033**	**0.034**	**0.040**	**0.058**
	(0.005)	(0.011)	(0.016)	(0.018)
Observations	**10962**	**10962**	**10962**	**9971**
R-squared	**0.03**	**0.06**	**0.07**	**0.07**

Models include hospital and year fixed effects; Robust standard errors in parentheses; Other vehicle types not shown; Omitted categories are head-on collision, motorcycle, bicycle & pedestrians, urban street, & large town.