Traffic Congestion and Accident Externality: A Japan-U.S. Comparison*

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Abstract

We measure the accident externality from driving in the spirit of Edlin and Karaca-Mandic (2006, JPE). We apply their empirical strategy to the prefecture-level panel data from Japan, and compare the results with those from the U.S. We find positive and statistically significant externalities in almost all prefectures, but the sizes are considerably smaller in Japan than those in the U.S. In Kyoto, for example, an additional driver increases accident costs of other drivers by $248-$807, whilst it is $1,725-$3,239 in California where the traffic density is approximately the same. *On a per-mile basis*, however, much closer external costs are obtained especially in the region where observations are not scarce. These findings indicate (i) that the extremely large externality reported by Edlin and Karaca-Mandic largely attributes to the fact that U.S. drivers travel comparatively a long distance, and (ii) that the estimation results from aggregate data set might be sensitive to the disturbances that are not successfully controlled, at least in the region where observations are scarce. Policy recommendations for internalizing the externality are also discussed.

Key words: accident externality, traffic congestion, auto insurance, Pigouvian tax

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1 Introduction

The intriguing and controversial article by Edlin and Karaca-Mandic (2006) (EK, hereafter) has proposed remarkable findings about accident externalities which negligence rules fail to internalize. Using a panel-data set of U.S. states, they demonstrate that the accident externality from driving is considerably large in high density roads, whilst it is quite small in low density roads. According to their study, in California, for example, an additional driver on the road increases other drivers' insurance costs by \$1,725 - \$3,239 annually, but the figure is as small as $\$-46$ - \$10 in North Dakota. Overall, they conclude, the accident externality is so large that a Pigouvian tax amounts to over \$220 billion per year nationally (for the year of 1996) which is even larger than the combining corporate and individual income taxes (\$163 billion) in the same year.

EK, to our thoughts, deserves a further investigation not only because it provides academically interesting findings, but also because it encompasses some valuable policy implications.[1] For instance, EK highlights the seriousness of the widely-recognized shortcoming of tort law. As formally analyzed by Shavell (1980) and Polinsky (1980), any form of negligence rule (simple, contributory, comparative, or some combinations of these rules) cannot achieve the socially optimal level of "activity", whilst it can achieve the optimal level of "precaution (care)". This well-known shortcoming of negligence rule has now revealed to be an unignorable defect which ought to be corrected in some manner.

Another important implication of EK is that their finding of large accident externalities has opened up a new direction of traffic safety policy. The strictly positive and statistically significant

[1]Although EK has evoked a wide range of arguments, empirical studies on the accident externality is rather a classical topic in economics. It dates back to at least Vickrey (1968) and Haverman (1973), and a number of empirical studies have been proposed to date. They include Newbery (1987), Jansson (1994), Persson and Ödegaard (1995), Peirson, Skinner, and Vickerman (1998), and Lindberg (2001), among others. It seems that empirical studies on congestions have been comparatively active in Europe.

relationship between the traffic density and accident costs indicates that the traffic congestion is one of the most significant sources of accident costs, and there is a large room for decreasing accident costs by controlling the traffic volume. This finding is of extreme importance, since motor vehicle accidents are still in a tragic situation in many countries, and reducing the number of victims has been a major public concern.[2] The authority has adopted a variety of regulations, but the traffic congestion has comparatively been paid little attention as a source of auto accidents. EK's finding represents a new step on the way to reduce accidents via controlling the traffic volume.

The purpose of this paper is to provide complementary evidence on the accident externality from driving. We apply EK's empirical strategy to the prefecture-level data set from Japan over the period 1980-2002, and provide the estimation results in such a way that they can be directly compared with the results from the U.S. This procedure not only enables us to provide additional evidence on accident externalities from a different country, but also leads to shed more lights on the EK's findings in the U.S.[3]

Our major findings can be summarized as follows. Consistent with the results from the U.S., we

[2]In 2002, 42,815 and 9,575 lives were lost in the U.S. and Japan, respectively. Cabinet Office, Government of Japan, estimates that the total loss cost by traffic accidents is $39.5 billion in 1999 which constitutes 0.87 percent of gross domestic product. (*Kotsu Jiko ni yoru Keizaiteki Sonshitsu ni kansuru Chosa Kenkyu* ("Research on the economic loss from traffic accidents," in Japanese.) Here, loss costs include both personal injury and physical damage costs, as well as various other costs associated with accidents.

[3]One possible view of our findings is to take them as the results from more "refined" data set than that used in EK. The data are more "refined" in the following two senses. One is that each sample of our data covers much narrower region than those in the U.S. Japan is a country which covers slightly narrower region than the state of California does, and within the area, there are 47 prefectures. This means that our prefecture-level data set from Japan can be regarded as a county level or slightly broader level data (for a reference, there are 58 counties in California).

The other desirable feature of our data is that they are free from the "auto insurance crisis" in the U.S. It is well known that the auto insurance premiums and costs increased enormously in some states during the 1980s and 1990s. The problem was extremely severe in the states such as California, Massachusetts, and New Jersey, all of which EK has found substantially high accident externalities. As we will see more closely in section 3, auto insurance premiums and costs not only were systematically high but also fluctuated dramatically in those states, suggesting that the effects of the "auto insurance crisis" were not fully controlled by control variables and a panel structure. The Japanese auto insurance market, on the other hand, did not experience this kind of unusual cost and premium surge, and therefore it is free from this problem.

However, we are not inclined to lay strong emphasis on these aspects, partly because we do not know how much these problems are mitigated by state-specific effects and year dummies, and partly because we believe that the Japanese data still covers too broad territories.

find positive and statistically significant accident externalities in almost all prefectures in Japan. The sizes of accident externalities per vehicle, however, are found to be significantly smaller in Japan than those in the U.S. In Kyoto, for example, the yearly external cost of marginal driver is calculated as $248-$807 which is considerably smaller than the estimates in California ($1,725-$3,239) where the traffic density is approximately the same. The gap becomes even larger in more crowded regions, and because of this disparity, a nationwide Pigouvian tax amounts to $16-$51 billion per year which is also by far smaller than the corresponding figure in the U.S. ($220 billion).

On a per-mile basis, however, we find much similar accident externalities between Japan and the U.S. In Florida, for example, the accident externality from additional one mile of driving is measured as $.070, while it is $.067 in Gunma which has the similar traffic density. This finding, however, no more persists in the range (approximately over 700,000 vehicle miles/lane miles-year) where the number of observations is small.

The above two basic findings provide additional important implications as follows. First, the surprisingly large accident externality (per vehicle) found by EK largely attribute to the fact that the U.S. drivers travel a long distance on average. The U.S. drivers travel 1.75 times as much as Japanese drivers, and it directly affects the estimation results of the accident externality per vehicle. Second, the bias from aggregate data might be small in the range where there are many observations, but it can be substantial in the range where the number of observations is small.

The remainder of the paper is organized as follows. In Section 2, we introduce the data set and report the estimation results on accident externalities. In Section 3, we discuss the desirability and feasibility of a Pigouvian tax on auto insurance as a mean of internalizing accident externalities as well as some other alternative policies. In Section 4, concluding remarks are presented.

2 Accident Externality in Japan

In this section, we measure the accident externality from driving using the data set from Japan. We first introduce the data and provide some preliminary analyses, and then provide the estimation results of accident externalities following EK's empirical procedure. Throughout this section, we refer to the discussion paper version of EK, Edlin and Karaca-Mandic (2003) that provides more comprehensive findings.

2.1 Data

The data set used in this study is a prefecture-level panel data set from Japan over the period 1980-2002. We collect data on insurance cost, traffic density, and a variety of control variables which are the same as those used in EK. In the following part, however, we only elaborate insurance cost (*cost*) and traffic density (*density*), since they play a crucial role in this study. For the information about the definitions and sources of other variables, see Data Appendix.

A. Data on Accident Cost

Following EK, we use auto insurance data as a proxy for accident loss (*cost*).[4] EK uses both insurance premium and loss payment, but we only use insurance loss payment. This is because insurance premiums do not reflect accident costs in Japan, since the rate regulation had prevented insurance companies from discriminating by region until the partial deregulation in 1998.[5]

[4]Making use of auto insurance data as a proxy for accident cost is clearly one of the most brilliant ideas of EK. Accident cost is often hard to measure on a monetary basis especially in the case of bodily injury, and even if it is measured in some way, it would be vulnerable to a variety of factors. Indeed, de Blaeij, Raymond, Rietveld, and Verhoef (2003) finds that there is a significant disparity between stated and revealed preference studies in estimating the value of statistical life (VSL), and the result largely depends on the empirical method adopted. See also Viscusi and Aldy (2003) for the measurement issues of VSL. Since auto insurance loss is calculated on the market basis, it would be one of the most appropriate proxies available, if not perfect.

[5]For more information about the institutional aspect of the Japanese auto insurance market, see Dionne (2002) and Automobile Insurance Rating Organization (2002).

Auto insurance in Japan consists of compulsory and voluntary insurance, and compulsory insurance covers only bodily injury liability up to a certain upper limit, and all the other types of accident loss are covered by voluntary insurance contract. Basically, voluntary insurance covers four major types of accident losses: bodily injury liability, property damage liability, passenger's personal injury, and collision damage. We define accident loss as the sum of compulsory and voluntary insurance, the latter of which includes all those four types of coverage.[6]

The data on insurance cost come from the following three sources which describe the summarized version of auto insurance statistics for each prefecture: *"Jibaiseki Jido-sha Hoken Tokei"* (Compulsory Automobile Insurance Statistics), *"Jido-sha Hoken Tokei"* (Automobile Insurance Statistics (Written Basis)), and *"Jido-sha Hoken no Gaikyo"* (Survey of Automobile Insurance). All of these statistics are collected and made available to the public by a nonprofit organization, named Non-Life Insurance Rating Organization of Japan.

One caveat deserves mention. In our data set, 64.8 percent of drivers have voluntary insurance in 1995, and the penetration rate is the highest in Osaka (81.3 percent) and the lowest in Okinawa (48.5 percent). These figures raise two concerns. First, 64.6 percent of the average penetration rate suggests that there would be a substantial number of accidents which are not covered by our data set. More specifically, two major types of accidents are likely to be dropped out from our data; (i) accidents caused by drivers who have no voluntary insurance, and (ii) accidents caused by drivers who purchased fraternal insurance ("Kyosai Hoken" in Japanese) which is mainly offered either by consumer's cooperative unions or farmer's cooperative unions. The other concern comes from the large disparity in penetration rate. This could be a problem because the accident externality will

[6] EK's insurance cost data cover bodily injury, property damage, and passenger's personal accident, and their insurance premium data cover liability and collision insurance (comprehensive premium is excluded). Therefore, our data is more comprehensive than the U.S. data.

be overestimated if there is a positive correlation between penetration rates and traffic densities.[7] This positive correlation is likely to exist in Japan, since fraternal insurance is more popular in rural areas where the traffic density tends to be low. To address these problems, we multiply the reciprocal of penetration rate of bodily injury liability insurance, assuming that there is no systematic difference in driving behavior between insured and uninsured drivers.[8]

Using these data sets, we construct a proxy for accident costs by dividing insurance payment either by the number of vehicles (*car*) or by vehicle-mile traveled (*vmt*).

B. Data on Traffic Density

Traffic density (*density*) is defined as vehicle-mile traveled (*vmt*) divided by lane mile (*lane*). Vehicle-mile-traveled data (*vmt*) is based on the survey conducted by Ministry of Land, Infrastructure and Transport Japan (MLIT). MLIT conducts random sampling survey on 30,000 vehicles every year, and asks various questions including annual mileage traveled. A national summary of the statistics is made available to the public in "*Jido-sha Yuso Tokei Nenpo*" (Motor Vehicle Transport, Annual).[9] This national vehicle-mile traveled data is translated into prefecture data

[7]Edlin and Karaca-Mandic (2006) does not take into account the difference in penetration rate of auto insurance. It could lead to an overestimation of accident externality in the case of insurance cost per mile driven models; In those models, the dependent variable is defined as insurance costs divided by vehicle-mile traveled. Here, the numerator only includes those who have auto insurance, but the denominator includes all drivers. If the penetration rates of auto insurance in high-density states are higher than those in low-density states, it would result in a positive correlation between the traffic density and accident costs which will lead to overestimate the accident externality. Insurance premium models, however, will be free from this problem, because the dependent variable is defined as insurance premiums divided by the number of insured drivers.

Also, the availability of the data on PIP insurance could also lead to a biased result. According to the original data "*Trends in Auto Injury Claims*" by Insurance Research Council, the data on PIP is available for 19 states out of 50 states in 1996, and not available for the remaining 31 states. Because many high-density states report PIP insurance, it could lead to overestimate the accident externality.

[8]For example, in the case of Osaka where the penetration rate is 81.3 percent, we multiply insurance loss payment by $\frac{100}{81.3}$. One might concern the possibility of adverse selection and/or moral hazard which will underestimate accident costs. Recent empirical studies, however, suggest that both of these problems are not severe in auto insurance market, whilst some studies find small but statistically significant evidence of adverse selection and/or moral hazard. (see Saito (2006, 2007) for the case of Japan, and Cohen and Dehejia (2004) and Israel (2004) for positive evidence of informational asymmetry.

[9]For more detailed information about this survey, visit `http://toukei.mlit.go.jp/jidousya/jidousya.html`. Data from 1980 to 1985 do not include the data on express highway. This point, however, will not have significant

by distributing the national value into each prefecture in proportion to the road traffic count data which is reported in MLIT's "*Doro Kotsu Census*" (Road Traffic Census) for every several years for each prefecture.[10] This variable can be interpreted as the distance traveled by all the types of vehicles in a given year.

Lane mile data comes from "*Doro Tokei Nenpo*" (Road Statistics Annual). The original data do not include length of lanes, but include length of roads by several categories of road width. We estimated lane miles as follows. Road whose width is between 5.5-13m is assumed to have two lanes and lane mile for that road-width category is generated by doubling the length of road. Lane miles for other width-categories were generated similarly.[11] We then summed up those lane miles over all the road-width categories.

Using this data set, we construct the data on traffic density (*density*) by dividing vehicle-mile traveled by lane mile.

2.2 Preliminary Analysis

Table 1 contains summary statistics on accident costs and densities, as well as variables used as control variables. We convert all the monetary values to 1996 dollars, so that we can directly compare them with variables from the U.S. Roughly speaking, in the U.S., there are three times as many vehicles as in Japan, roads are six times as long as Japanese roads, and people travel 1.75 times as much distance as Japanese drivers. The average traffic density is 581,793 vehicle-mile/lane year in 1995, indicating that the roads in Japan are 1.82 times as much crowded as roads in the U.S. However, one should be careful in the interpretation of this figure as we will se below.

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effects on our results because it accounts for only a small percentage of total lane miles.

[10]The road traffic count data are only available for major roads. We assume that the road traffic distributions over prefectures are the same between the major routes and all the roads.

[11]The relationship between the width of road and the number of lanes is assumed as follows (width (#lane)): over 19.5m (6), 13-19.5m (4), 5.5-13m (2), and under 5.5m (1)

Figure 3 represents a graphical exposition of the distribution of the traffic density and insurance costs for Japan and the U.S. It shows that the average traffic density does not convey sufficient information about the difference in the traffic density; the higher average traffic density in Japan is due the fact that, in Japan, there are not so much roads that have low-densities. Even in the least crowded prefecture, the density is over 300,000 vehicle-mile traveled per lane-mile in 1995, which is close to the U.S. average traffic density. It also shows that only Tokyo and Osaka are more crowded than the most crowded state (Hawaii) in the U.S., which might be a somewhat surprising finding. We can also confirm that the insurance cost per mile driven is slightly higher in Japan holding the traffic density constant. The relationship between the traffic density and accident costs seems to be positive, but it is not very much clear only from the scatter plots.

2.3 Regression

In order to control other factors which will affect accident costs, we estimate the following regression model which is exactly the same as equation (6) in EK;

$$cost_{it} = \alpha_i + \gamma_t + c_1 + c_2 D_{it} + c_3 D_{it}^2 + \mathbf{b x_{it}} + \epsilon_{it} \tag{1}$$

where $cost_{it}$ is accident cost in prefecture i in year t, α_i is prefecture fixed effect, γ_t is the time fixed effect, D_{it} is the traffic density, $\mathbf{x_{it}}$ is a set of control variables equally defined as those in EK, and ϵ_{it} is error term. The dependent variable $cost_{it}$ is defined either as the "accident cost per vehicle" ($cost/car$) or as the "accident cost per mile driven" ($cost/vmt$), and the quadratic term $c_3 D_{it}^2$ will be omitted in a linear model. We are interested in the coefficients on D_{it} and D_{it}^2.

Table 2 presents the estimation results of equation (1). We have run both naive OLS and instrumental variable regressions which take into account the potential bias from the measurement error, but we only report the results from IV regressions since they provide more reliable estimates than those from OLS because of the measurement error problem.[12]

Let us begin with checking the relevance and the exogeneity of instruments since the reliability of the coefficient estimates hinges largely on the validity of instruments. First, in all models, Durbin-Wu-Hausman test of endogeneity rejects the null of no endogeneity, suggesting that *density* is endogenous and IV method will be required. Second, in all equations, large first stage F-statistics show that instruments are not weak. Finally, J-statistics for over-identifying restrictions tell us that we cannot reject the null of instrument variables being exogenous in all models. Now that we have confirmed the validity and exogeneity of instrumental variables, we can rely on the standard methods for statistical inference using the estimated coefficients and standard errors.

Columns (a) and (b) contain estimation results using insurance cost per vehicle as a dependent variable. In both linear and quadratic models, the coefficients on density (D) and its squared values (D^2) are statistically significant at one percent level, except for one on D in model (b). At the same time, however, we can confirm that the sizes of coefficients are considerably smaller than those from the U.S.; for instance, in linear model, our coefficient is 0.00045, whilst it is 0.0019 in EK (see column (3) of Table 2, p.942).

In Columns (c) and (d), we report estimation results using the insurance cost per mile driven as a dependent variable. Again, the coefficients on density and its squared value are statistically significant at one percent level in both linear and quadratic models. We also confirm that the slope of quadratic function is less steep in Japan than in the U.S., although there is no corresponding model in EK for our model (c). These disparities of the estimated coefficients will play a crucial

[12] As found in EK, the coefficient on D becomes larger when we adopt instrumental variable method.

role in the measured accident externalities, as we will see in the next section.

Results on other variables are largely consistent with our intuition. Alcohol consumption per population, income per capita, and hospital costs, all of these factors have positive and statistically significant influence on accident costs. On the other hand, the table shows that the ratio of young male driver has only an ambiguous effect on accident costs, and precipitation and snow days have no statistically significant impact on accident costs.

2.4 Accident Externality

Having obtained the regression results, we now move on to the measurement of accident externalities. We first provide the estimation results of the accident externality per driver, and then provide the results of the externality per mile driven.

A. Accident Externality per Driver

Following EK, we define the accident externality per driver as $\hat{c_2}D$ for model (a), $\hat{c_2}D + 2\hat{c_3}D^2$ for model (b), $\hat{c_2}D \times (\frac{M}{N})$ for model (c), and $(\hat{c_2}D + 2\hat{c_3}D^2) \times (\frac{M}{N})$ for model (d).

Table 3 reports computed accident externalities for all prefectures, and Table 4 presents externalities for selected prefectures. The results show that, in almost all prefectures, positive and statistically significant accident externalities exist. In Osaka, where the traffic density is the highest, the yearly cost of additional driver is estimated to be \$593-\$1,927, and even in the least crowded prefecture, Hokkaido, it is estimated to be \$42-398.

When the results are compared with those from the U.S., however, one important feature arises; Accident externalities in Japan are considerably smaller than those in the U.S. For instance, Kyoto is as much crowded as California (748,431 and 728,974 vehicle-mile traveled/lane-mile in 1996, respectively), but the accident externality is estimated to be \$248-\$807 in Kyoto and \$1,725-\$3,239 in California respectively. The disparity becomes even larger in more crowded regions. In Hawaii, where the traffic density level is close to that in Kanagawa, the accident externality is estimated to be \$1,831-\$3,933, whilst it is as small as \$367-\$841 in Kanagawa.

Figure 4 provides a visual exposition of these findings. As displayed in the figure, the disparity is a direct consequence of the different coefficients on D and D^2 in equation (1). The quadratic function of the U.S. is significantly steeper than that of Japan, and the gap becomes larger as the traffic density becomes higher.

Due to this disparity, a nationwide Pigouvian tax is also estimated to be \$16-\$51 billion in Japan, which is considerably smaller than the U.S. estimates, \$220 billion. Although a nationwide Pigouvian tax depends on the number of vehicles in a country, the gap cannot be compensated by the difference in the number of registered vehicles: 72,393 and 220,681 thousand in Japan and in the U.S. respectively (2002).

B. Accident Externality per Mile of Driving

So far, we have defined the accident externality on a per-vehicle basis. When we think over the fact that Japan is a country which only covers slightly narrower region than the state of California does, it is natural to expect that the Japanese drivers travel much shorter distance than the U.S. drivers on average. This aspect is worth being considered since the accident externality per vehicle is defined as $(\hat{c_2}D + 2\hat{c_3}D^2) \times (\frac{M}{N})$, where the average travel distance $(\frac{M}{N})$ directly comes in. In this section, we measure the accident externality *per mile of driving* in order to take into account this aspect.

Let us first look at the difference in the travel distance. Figure 5 displays the average travel distance in Japan and the U.S. in 1996. It shows a clear tendency that the U.S. drivers travel significantly longer distance. The average annual travel distance is 12,117 miles in the U.S. and 6,913 mile in Japan, suggesting that the U.S. drivers travel 1.75 times as long distance as Japanese drivers.[13]

Another interesting feature of Figure 5 is that the average travel distance is largely dispersed *within* the country. For example, people travel more than 15,000 miles per year in the states such as Alabama, Arkansas, and Kentucky, but people travel less than 10,000 miles in the states such as Iowa, Montana, North Dakota, and New Hampshire. These observations suggest that people living in the states with vast territories do not necessarily travel longer distance, indicating that not only geographic conditions but also a variety of conditions, such as driving patterns and the availability of public transportation system, will affect average travel distance.

Having considerably different travel distances, we expect the per-mile accident externality is different from the per-vehicle externality. Figure 6 shows the accident externality per mile of driving. Here, we measure the per-mile externality by multiplying the accident externality per vehicle $\left((\hat{c_2}D + 2\hat{c_3}D^2) \times (\frac{M}{N})\right)$ by the reciprocal of the average travel mile $(\frac{N}{M})$ where N is defined as the number of registered vehicles.[14] In order for the results to be compared with those from the U.S., we use the results from model (d) in Table 2.

There are two important features about the figure. One is that, from around 30,000 to 70,000 vehicle-mile traveled per lane mile, the accident externality per mile of driving is quite similar in Japan and the U.S. For example, the accident externality per mile is measured as \$.070 in Florida,

[13]It would be worth investigating whether the American (Japanese) drivers travel exceptionally long (short) distance. Table 5 provides an answer for this question. Among the countries listed in the table, the U.S. drivers travel the longest distance and Japanese drivers travel the shortest. This indicates that the different findings between the per-vehicle basis externality and per-mile basis externality are partly due to the fact that we are focusing on the two different countries which have substantially different annual mileage.

[14]See p.938 of Edlin and Karaca-Mandic (2006) for more detailed discussion. Note that we define N as the number of registered vehicles in both countries, not the number of licensed drivers. This is mainly because reliable data on the licensed drivers were not available for some of the U.S. states.

which is quite similar to the corresponding figure in Aomori ($.067) whose traffic density is close to that of Florida.[15] Although the results largely disperse in Japan, the externalities are much similar to each other, compared with the results from a per-vehicle analysis. One important implication of this finding is that the extremely large accident externality reported by EK largely attributes to the fact that the U.S. drivers travel comparatively long distance.

The other important feature of Figure 6 is that the disparity becomes substantially large in the regions where the number of observations is small. In Hawaii, for example, the per-mile externality is calculated as $.33, but it is as small as $.12 in Kanagawa which has similar traffic density.

Where does this disparity come from? Whilst there would be various answers for this question, we conjecture that it mainly comes from the fact that both of the studies rely on aggregate data, and therefore there remains a variety of factors which are not successfully controlled. For example, the effects of "auto insurance crisis" in the U.S. might not be successfully controlled. In the 1980s and 90s, auto insurance premiums and costs surged enormously in some states, and the problem was extremely severe in the states such as California, New Jersey, Massachusetts, and Hawaii,

[15] One might wonder whether these estimated externalities per mile of driving are large or small. To answer this question, let us consider a situation where a Pigouvian tax is levied on gasoline. Suppose that an average driver possesses a car which runs 30 miles per gallon. (These figures come from an observation that the fuel cost of Honda Accord Sedan is 26/34 mpg.) Also, let us assume that gasoline price is $2.5 per gallon including all the taxes before the imposition of a Pigouvian tax. In California, for example, the accident externality per mile of driving is computed as $.22 per mile. Then the correcting Pigouvian tax should be $6.6 per gallon (fuel cost of 30 miles × $.22), which ends up with a significant increase of gasoline price up to $9.1 per gallon (264% increase). To the contrary, in North Dakota, a gasoline price after imposing a Pigouvian tax will be $2.44 per gallon, which is only slightly lower than the original price. These calculations show that accident externalities per mile of driving are quite large in high-density states, but small in low-density states, which is the same implications as those from the per-vehicle analysis.

A practical difficulty of imposing different Pigouvian tax on gasoline, however, is that a discriminatory Pigouvian tax across states will be eliminated by arbitrage trade. If a gasoline price is high in California and low in North Dakota, gasoline will be transferred from North Dakota to California, inasmuch as the cost of such transportation will become equivalent to the gains from filling the price gap. Therefore, in a realistic situation, we have to assume that a single Pigouvian tax rate is levied on the whole country. Now let us consider the same situation as in the previous paragraph. Since the national average of the accident externality per mile of driving is measured as $.04, driving 30 miles generates other drivers' accident costs by $1.2 (=30mpg × $.04). Therefore, a gasoline price which includes a correcting Pigouvian tax will become $3.7 (=$2.5 + $1.2) per gallon, which is 48 percent increase from the original price. This moderate amount of tax on gasoline, of course, is due to the fact that accident externalities are quite small in low density regions. It might also be informative to mention that Levitt and Porter (2001) finds "[t]he externality per mile driven by a drunk driver is at least 30 cents."(p.1198) all of which EK has found a large accident externality. While it is possible that the effect of this unusual cost surge is controlled by state fixed effects and year dummies, as shown in Figure 1 and 2, the average auto insurance premiums in those high-density states not only remained considerably higher than the U.S. average, but also dramatically fluctuated throughout the sample period, indicating that those effects might not be fully controlled. Since accident costs are defined as insurance premiums and payments, failing to control this unusual cost surge leads to over state accident externalities.[16]

3 Discussion

Although we have laid somewhat strong emphasis on the difference between Japan and the U.S., our study basically confirms EK's finding that the accident externality is substantially large in high-density regions. Given this large external cost, it would be worth discussing how to internalize it. In this section, we argue some possible solutions to the externality.

A Pigouvian Tax on Auto Insurance

EK argues that "the most efficient way to address the accident externality would probably be to levy a large tax on insurance premiums. A tax on insurance premiums, unlike a gas tax, would take into account heterogeneity because insurance premiums already do so."(p.952)

Their argument makes a lot of sense, since accident probabilities will vary significantly across

[16] A crucial question, of course, is whether the high insurance premiums and costs are the result of high accident costs. There have been many arguments regarding the reason for the incredibly high auto insurance premium and cost in these states, but it seems that there has been little general agreement on the determinants of cost surge so far. Some have argued the possibility of regulation failure including the reduction of incentives for cost control, and others have argued the change in the market structure (e.g. Blackmon and Zeckhauser (1991), Smith and Wright (1992), Jaffee and Russell (1998, 2002), Tennyson, Weiss, and Regan (2002), and Worrall (2002)). Also, Gron (1994) argues that capacity constraint has a significant effect on property casualty insurance premium by showing that unanticipated decrease in capacity lead to higher profitability and prices. Although we do not investigate the reason for the cost surge any further, this series of discussions indicates that the cost surge could be the result of various factors that are not related to accident costs.

drivers, and insurance companies have strong incentive to collect relevant information in order to set competitive premiums. If taxes are levied on gasoline, people will face the same amount of tax regardless of the accident propensity, and it will result in a policy that is both inefficient and unfair.

Imposing a heavy tax on auto insurance, however, raises one serious concern as long as it is levied on voluntary insurance; It can create a numerous number of uninsured drivers. Theoretically, raising a tax on "per mile auto insurance" will decrease the driver's action level, and lead to lower accident costs (because of the large accident externalities we have found). But one undesirable scenario goes as follows. If a tax on auto insurance is raised significantly, high-risk drivers, such as young male drivers, are no more afford to buy insurance, but they *will* drive as much as before, resulting in producing a sizable proportion of uninsured drivers on the road. This scenario is not unrealistic because the correcting Pigouvian tax could be quite large in high-density regions,[17] and because the auto insurance demand is known to be highly price elastic (see e.g. Jaffee and Russell (1998)). As symbolized by Proposition 103 in California in 1988, the pricing of auto insurance is a fairly delicate issue, and we have to be prudent in imposing a heavy tax on auto insurance.

Considering this potential concern as well as the current situation that the "per mile premium" is still not a common practice in many auto insurance markets, for the meantime, a Pigouvian tax on auto insurance does not seem to be a practical way of internalizing externalities.[18]

[17] According to Edlin and Karaca-Mandic (2006), "[i]n California, a Pigouvian tax might be roughly 200-400 percent". (p.952)

[18] Even if a Pigouvian tax on auto insurance is not a realistic policy, there seem to be several ways to take into account heterogeneity of drivers. For instance, the authority can adopt a discriminatory penalty on drunk driving which is heavier in California than that in North Dakota. This policy would be a fair policy, because statistical evidence shows that a heavy penalty works as an effective deterrence mechanism. For example, Bar-Ilan and Sacerdote (2004) reports that heavier fines for running red lights have enhanced deterrence especially for younger drivers. In addition, a heavy penalty for reckless driving could be effective especially in high-density regions, since many fatal and large-scale traffic accidents tend to be caused by reckless driving such as excessive speed, inattentive driving, and drunk driving. (For instance, Levitt and Porter (2001) estimates that drunk drivers are seven times more likely to have fatal accidents and legally drinking drivers cause 13 times as likely to have accidents as sober drivers.) Of

Public Transportation System

A Pigouvian tax on driving is not the only way to control the traffic volume. Although road constructions are not a promising idea in Japan, either, the availability and convenience of public transportation system will also affect the traffic volume, since it is a close substitute for private cars. It is natural to assume that the better transportation system (e.g. lower fares, higher frequencies, punctualities, more routes, improved safeties, more cleanliness, and so on) will shift a significant proportion of private car users to buses and subways.

A crucial problem of this policy, of course, is how to achieve this goal. Small (2005) proposes a somewhat paradoxical answer: a congestion charge. From the experience of congestion charge in London in 2003, he reports that there was a preferable interaction between the congestion charge and improved services. The desirable circle was feasible since the increased revenues by the congestion charge led to lower average costs per passenger, resulting in improved services and lower fairs. Of course, this preferable interaction relies on some ideal situations, and might not easily be generalized to other cities.

Strict Liability

Perhaps more fundamental approach to internalize accident externalities would be strict liability. As discussed in Shavell (1980, 1987) and Polinsky (1980), a strict liability rule leads to the socially optimal level of "action", at least theoretically. In addition, it will greatly reduce administrative costs compared to those under a negligence rule.[19] A reduction of administrative costs could be

course, however, a discriminatory penalty is not a policy which "internalizes" the accident externality, although it will affect people's decision about whether to drive and how much drive to a greater or lesser extent.

[19]Although the total administrative costs under strict liability and negligence rule is ambiguous at least theoretically, as far as traffic accidents are concerned, it seems natural to assume that the effect of average reduction of administrative cost is likely to dominate the effect of increase in the number of claims.

substantial especially in the case of motor vehicle accidents, considering a huge number of accidents that result in lawsuits. Although strict liability is not a common practice until now, it seems to be a reasonable rule at least in the case of auto-pedestrian accidents.[20]

Even if strict liability is applied only to auto-pedestrian cases, a simple observation shows that it will have a significant impact on the total number of accidents; As shown in Table 6, pedestrians and bikers constitute 42.7 percent and 12.7 percent of total fatally injured victims in Japan and the U.S. respectively. Given this large portion of pedestrian and biker victims, it is natural to expect that the change of a legal rule will have a large impact on driver's behavior.

4 Conclusion

In this paper, we set out to measure the accident externality from driving in the spirit of Edlin and Karaca-Mandic (JPE, 2006). Using the prefecture-level panel data over the period from 1980 to 2002, we find that accident externalities per vehicle are considerably smaller in Japan than those in the U.S. But *on a per-mile basis*, we obtain quite similar external costs, especially in the range where there are comparatively large observations. Important implications of these findings include (i) that the large accident externality (per vehicle) proposed by EK largely attributes to the fact that the U.S. drivers travel comparatively a long distance on average, and (ii) that the bias from aggregate data might be small in the range where there are many observations, but it could be substantial in the region where observations are scarce.

Considering the huge number of traffic victims, it is important to put our findings into practice. To do this, however, more detailed knowledge about the relationship between the traffic volume

[20] As long as one drives a car, there is a positive probability of injuring people however carefully he/she drives. On the other hand, there would be few people who want to be hit by a car even if his/her loss is fully compensated on a monetary basis. Then, on what grounds should a pedestrian be blame for that accident?

and accident costs would be indispensable. State-level and prefecture-level data sets might be able to provide rough sketches of the significance of the accident externality, but substantively, they cannot not go any further. Perhaps one of the most promising ways to achieve this goal is a social experiment. It enables us to control relevant factors successfully, which is imperative for obtaining reliable estimates. Indeed, a congestion charge imposed in London in 2003 has revealed a variety of important findings, such as the impact on the traffic volume, the change in the speed of each type of vehicles, the change in costs and revenues of public transportation systems, and the predictability of longstanding economic models (see e.g., Small (2004); Newbery (2005); Leape (2006)). Presumably, social experiments should be designed at a city or town level, considering the large disparity in geographic conditions and driving patterns.

Data Appendix

This appendix describes the definitions and sources of variables used in this study including variables used as instruments. All the monetary values are deflated using GDP deflator. Variables are listed in alphabetical order of variable names. For the U.S. data, see Edlin and Karaca-Mandic (2003).

- *alcohol* : Total alcohol consumption is divided by the number of total population. (gallon/person) Source: National Tax Agency, *"Kokuzei-cho Tokei Nenpo Syo"* (National Tax Agency Annual Statistics Report), in Japanese.
- *car* : Number of registered cars. Source: MLIT, *"Jido-sha Hoyu Syaryo Su"* (Number of Vehicle Possession), in Japanese.
- *cost* : Auto insurance cost. See section 2.1 for the details.
- *density* : Traffic density defined as $vmt/lane$.
- *gas_station* : Number of gas stations. Source: *"Sekiyu Tokei Nenpo"* (Annual), in Japanese.
- *income* : Income per capita. (dollar per capita) Source: *"Kenmin Keizai Keisan Nenpo"*, in Japanese.
- *lane* : Total lane mile. See section 2.1 for details.

- *med* : Average amount of cost of hospitalization per day per person. Source: *"Kokumin Kenko Hoken Jigyo Nenpo"* (National Medical Insurance Annual), in Japanese.

- *rain* : Amount of rainfall (inches/year). Source: *"Kisyo-cho Tokei Nenpo"* (Annual Report of the Japan Meteorological Agency), in Japanese.

- *snow* : Number of days with snowfall. Source: *"Kisyo-cho Tokei Nenpo"* (Annual Report of the Japan Meteorological Agency), in Japanese.

- *population* : Number of total population. Source: Population Census and estimates based on the Population Census (total population) and Doro Tokei Nenpo (lane mile).

- *popdens* : Population density, defined as (*population* / *lanemile*).

- *vmt* : Vehicle mile traveled. See section 2.1 for details.

- *young* : Percentage of male aged 15-24 (%). Source: Bureau of Statistics *"Jyumin Kihon Daicho"*, (Basic Resident Registers), in Japanese.

References

Automobile Insurance Rating Organization (2002): "Automobile Insurance in Japan," (booklet in English).

Bar-Ilan, A., and B. Sacerdote (2004): "The Response of Criminals and Noncriminals to Fines," *Journal of Law & Economics*, 47, 1–17.

Blackmon, B. G., and R. Zeckhauser (1991): "Mispriced Equity: Regulated Rates for Auto Insurance in Massachusetts," *American Economic Review*, 81(2), 65–69.

Cohen, A., and R. Dehejia (2004): "The Effects of Automobile Insurance and Accident Liability Laws on Driving Behavior and Traffic Fatalities," *Journal of Law & Economics*, 47(2), 357–393.

de Blaeij, A., J. Raymond, P. Rietveld, and E. T. Verhoef (2003): "The Value of Statistical Life in Road Safety: A Meta-Analysis," *Accident Analysis and Prevention*, 35(6), 973–986.

Dionne, G. C. (2002): "Insurance Regulation in Other Industrial Countries," in *Deregulating Property-Liability Insurance*, ed. by J. D. Cummins, pp. 361–396. AEI-Brookings Joint Center for Regulatory Studies, Washington D. C.

Edlin, A. S., and P. Karaca-Mandic (2003): "The Accident Externality from Driving," Working Paper no. E03-332, Univ. California, Berkeley, Dept. Econ.

——— (2006): "The Accident Externality from Driving," *Journal of Political Economy*, 114(5), 931–955.

Gron, A. (1994): "Capacity Constraints and Cycles in Property-Casualty Insurance Markets," *Rand Journal of Economics*, 25(1), 110–127.

Haverman, R. (1973): "Common Property, Congestion, and Environmental Pollution," *Quarterly Journal of Economics*, 87, 278–287.

Israel, M. (2004): "Do We Drive More Safely When Accidents are More Expensive? Identifying Moral Hazard from Experience Rating Schemes," Northwestern University, The Center for the Study of Industrial Organization, Working Paper 0043.

Jaffee, D. M., and T. Russell (1998): "The Causes and Consequences of Rate Regulation in the Auto Insurance Industry," in *The Economics of Property-Casualty Insurance*, ed. by D. F. Bradford, pp. 81–112. The University of Chicago Press, Chicago.

——— (2002): "Regulation of Automobile Insurance in California," in *Deregulating Property-Liability insurance*, ed. by D. J. Cummins, chap. 5, pp. 195–236. AEI-Brookings Joint Center for Regulatory Studies, Washington D.C.

Jansson, J. O. (1994): "Accident Externality Charges," *Journal of Transport Economics and Policy*, 28, 31–43.

Leape, J. (2006): "The London Congestion Charge," *Journal of Economic Perspectives*, 20(4), 157–176.

Levitt, S. D., and J. Porter (2001): "How Dangerous Are Drinking Drivers?," *Journal of Political Economy*, 109(6), 1198–1236.

Lindberg, G. (2001): "Traffic Insurance and Accident Externality Charges," *Journal of Transport Economics and Policy*, 35(3), 399–416.

Newbery, D. (1987): "Road User Charges in Britain," *The Economic Journal*, 98(390), 161–176.

——— (2005): "Road Pricing: Lessons from London," Cambridge University and CEPR Economic Policy 42nd Panel Meeting (Bank of England London).

Peirson, J., I. Skinner, and R. Vickerman (1998): "The Microeconomic Analysis of the External Costs of Road Accidents," *Economica*, 65(259), 429–440.

Persson, U., and K. Ödegaard (1995): "External Cost Estimates of Road Traffic Accidents: An International Comparison," *Journal of Transport Economics and Policy*, 29(3), 291–304.

Polinsky, A. M. (1980): "Strict Liability versus Negligence in a Market Setting," *American Economic Review*, 70, 363–367.

Saito, K. (2006): "Testing for Asymmetric Information in the Automobile Insurance Market under Rate Regulation," *Journal of Risk & Insurance*, 73(2), 335–356.

——— (2007): "Does Asymmetric Information Matter in the Early Insurance Market? Evidence from the Auto Insurance Market," *Applied Economics*, forthcoming.

Shavell, S. (1980): "Strict Liability versus Negligence," *Journal of Legal Studies*, 9, 1–25.

——— (1987): *Economic Analysis of Accident Law*. Harvard University Press, Cambridge, MA.

Small, K. A. (2004): "Road Pricing and Public Transport," in *Research in Transport Economics*, ed. by G. Santos, vol. 9, pp. 133–158. Elsevier.

——— (2005): "Unnoticed Lessons from London: Road Pricing and Public Transit," Access, No.26.

Smith, E., and R. Wright (1992): "Why Is Automobile Insurance in Philadelphia So Damn Expensive?," *American Economic Review*, 82(4), 756–772.

Tennyson, S., M. A. Weiss, and L. Regan (2002): "Automobile Insurance Regulation: The Massachusetts Experience," in *Deregulating Property-Liability Insurance*, ed. by D. J. Cummins, chap. 2, pp. 25–80. AEI-Brookings Joint Center for Regulatory Studies, Washington D.C.

Vickrey, W. (1968): "Automobile Accidents, Tort Law, Externalities, and Insurance: An Economist's Critique," *Law and Contemporary Problems*, 33(3), 464–487.

Viscusi, K. W., and J. E. Aldy (2003): "The Value of a Statistical Life: A Critical Review of Market Estimates throughout the World," *Journal of Risk and Uncertainty*, 27(1), 5–76.

Worrall, J. D. (2002): "Private passenger Auto insurance in New Jersey," in *Deregulating Property-Liability Insurance*, ed. by D. J. Cummins, chap. 3, pp. 81–134. AEI-Brookings Joint Center for Regulatory Studies, Washington D.C.

Table 1: Summary Statistics (1987, 1995)

		1987				1995			
Variable	Unit	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
lane	lane-mile-year	15546.6	10856.0	5345.6	73542.5	17068.13	11770.23	6.02E+03	80265
vmt	vehicle-miles	7.30E+09	4.64E+09	2.47E+09	1.95E+10	9.58E+09	5.91E+09	3.20E+09	2.49E+10
cost	$/insured car-year	356.72	56.74	224.65	460.32	501.78	79.74	305.19	681.41
density	vehicle-miles/lane-mile-year	488,479	177,514	252,665	1,187,261	581,793	200,756	304,451	1,349,031
alcohol	gallon/person-year	16.104	2.083	12.91	23.751	19.67	2.48	15.86	28.54
income	$/per capita	16.80	2.58	13,393	27,301	29,222	3,917	21,935	43,432
young	%	6.70	1.06	5.00	10.00	7.13	0.72	5.85	8.54
med	$/patient-day	101.79	10.15	84.32	129.90	158.27	16.81	127.72	195.07
rain	inches/year	58.50	21.77	21.89	108.62	60.75	18.03	33.27	108.58
snow	days/year	35.89	33.20	0.00	130.00	35.04	34.91	0.00	130.00

Notes: All dollar values are in 1996 dollars deflated with the fixed-weighted GDP deflator and exchange rate. Variable definitions and their sources are described in Data Appendix. The actual alcohol consumption should be higher because total alcohol consumption is divided by total population, not by the population above the legally admitted age of 20. Alcohol consumption includes *mirin* (sweet cooking rice wine).

Table 2: Linear and Quadratic Insurance Cost Model: 1980-2002

	Dependent Variable Insurance Cost per Vehicle		Dependent Variable: Insurance Cost per Mile Driven	
	Linear Model (IV) EK's Model (3) in Table 2	Quadratic Model (IV) EK's Model (7) in Table 3	Linear Model (IV) no corresponding model	Quadratic Model (IV) EK's Model (10) in Table 3
Independent Variable	(a)	(b)	(c)	(d)
Density	0.000454***	−0.0000051	1.72E-07***	8.46E-08***
	(0.000063)	(0.0001205)	(2.53E-08)	(2.99E-08)
Density^2	—	2.25E-10***	—	6.94E-14***
		(5.75E-11)		(2.13E-14)
Alcohol	1.79***	1.81***	0.00051***	0.00054***
	(0.30)	(0.47)	(0.00016)	(0.00014)
Income	0.011***	0.011***	2.10E-06***	1.79E-06***
	(0.001)	(0.001)	(3.40E-07)	(3.19E-07)
Hospital	1.23***	1.14***	0.00028***	0.00017***
	(0.25)	(0.26)	(0.00006)	(0.00007)
Young_Male	1.423	4.33**	−0.00088	−0.00024
	(2.109)	(2.13)	(0.00063)	(0.00062)
Rain	0.020	0.025	2.45E-06	1.08E-06
	(0.092)	(0.091)	(1.85E-05)	(1.84E-05)
Snow	−0.094	0.0030	-1.98E-05	-3.89E-06
	(0.122)	(0.1225)	(3.00E-05)	(3.05E-05)
prefecture dummy	yes	yes	yes	yes
year dummy	yes	yes	yes	yes
Observations	1,080	1,080	1,080	1,080
R-sq	.9245	.9343	.8672	.9349
Wu-Hausman Test	30.24038	22.91128	195.0917	41.02631
of Exogeneity	$p = .00$	$p = .00$	$p = .00$	$p = .00$
Instrumental Variables	#car / lane	#car / (lane)^2	#car / (lane)^2	#car / lane
	#population / lane	#gas_station / lane	#population / lane	(#car / lane)^2
		(#gas_station / lane)^2		(#gas_station / lane)^2
First-stage F-statistic	$F(2, 1003) = 167.88$	$F(3, 1002) = 67.18$ (for D)	$F(2, 1003) = 143.12$	$F(3, 1002) = 412.72$ (for D)
	p-value = .00	p-value = .00	p-value = .00	p-value = .00
		$F(3, 1002) = 366.27$ (for D^2)		$F(3, 1002) = 445.62$ (for D^2)
		p-value = .00		p-value = .00
Hansen's J-statistic for	2.211	.793	.765	.024
over-identifying restrictions	p-value = .137	$p$value = .3733	p-value = .3818	p-value = .8758

Notes: *** and ** denote statistically significant at 1 and 5 percent level, respectively.
Newey-West heteroskedasticity-autocorrelation consistent standard errors are reported in the parentheses.
F-statistics display the value of test statistics for the null hypothesis that coefficients of all variables excluded from the Insurance Cost model are zero.

Table 3: External Accident Cost of Marginal Driver (1996)

			Insurance Cost per Vehicle Model				Insurance Cost per Vehicle Mile Model				
			Linear Model (a) EK's Model (3) in Table 2		Quadratic Model (b) EK's Model (7) in Table 3		Linear Model (c) no corresponding model		Quadratic Model (d) EK's Model (10) in Table 3		
	Prefecture	Traffic Density (1996)	$/driver	s.e.	$/driver	s.e.	$/driver	s.e.	$/driver	s.e.	#Vehicles
1	Hokkaido	309,730	140	(19)	42	(29)	398	(58)	294	(49)	3,377,432
2	Iwate	341,378	155	(21)	51	(32)	530	(77)	404	(63)	881,294
3	Akita	351,565	159	(22)	54	(32)	458	(67)	353	(54)	766,054
4	Kagoshima	352,097	160	(22)	54	(32)	377	(55)	291	(44)	1,148,443
5	Shimane	369,961	168	(23)	60	(34)	539	(79)	424	(62)	487,675
6	Aomori	395,573	179	(25)	68	(35)	442	(65)	357	(50)	894,833
7	Miyazaki	399,150	181	(25)	70	(36)	452	(66)	366	(51)	806,821
8	Nagano	445,373	202	(28)	87	(38)	521	(76)	441	(57)	1,682,493
9	Fukushima	447,430	203	(28)	88	(39)	586	(86)	497	(64)	1,406,191
10	Nagasaki	454,258	206	(29)	91	(39)	497	(73)	424	(54)	820,474
11	Kochi	458,759	208	(29)	92	(39)	573	(84)	491	(63)	523,193
12	Kumamoto	465,125	211	(29)	95	(40)	570	(83)	492	(62)	1,142,002
13	Tokushima	473,780	215	(30)	99	(40)	584	(85)	508	(63)	557,594
14	Niigata	488,511	222	(31)	105	(41)	667	(98)	588	(72)	1,628,965
15	Oita	502,001	228	(32)	111	(42)	683	(100)	609	(73)	775,484
16	Yamagata	520,750	236	(33)	119	(43)	688	(101)	624	(74)	844,208
17	Toyama	524,088	238	(33)	121	(43)	643	(94)	585	(69)	795,533
18	Ehime	525,826	238	(33)	122	(43)	612	(90)	558	(65)	904,137
19	Gunma	526,263	239	(33)	122	(43)	552	(81)	503	(59)	1,552,862
20	Gifu	532,817	242	(34)	125	(44)	679	(99)	622	(72)	1,478,325
21	Miyagi	539,279	245	(34)	128	(44)	638	(93)	588	(68)	1,401,801
22	Okayama	542,896	246	(34)	130	(44)	680	(99)	629	(73)	1,326,783
23	Tottori	546,379	248	(34)	132	(44)	784	(115)	727	(84)	406,120
24	Ibaraki	549,729	249	(35)	133	(44)	660	(97)	614	(70)	2,104,186
25	Ishikawa	550,920	250	(35)	134	(45)	677	(99)	631	(72)	777,792
26	Fukui	568,706	258	(36)	143	(46)	792	(116)	749	(85)	582,580
27	Wakayama	582,026	264	(37)	149	(46)	628	(92)	600	(67)	688,162
28	Hiroshima	590,869	268	(37)	154	(47)	701	(103)	675	(75)	1,649,144
29	Tochigi	603,138	274	(38)	161	(47)	755	(110)	735	(81)	1,425,134
30	Chiba	622,373	282	(39)	171	(49)	576	(84)	570	(62)	3,065,280
31	Mie	631,045	286	(40)	176	(49)	827	(121)	823	(90)	1,276,951
32	Kagawa	638,447	290	(40)	180	(50)	740	(108)	741	(81)	675,482
33	Nara	639,999	290	(40)	181	(50)	657	(96)	658	(72)	741,297
34	Fukuoka	665,862	302	(42)	196	(51)	671	(98)	687	(74)	2,835,064
35	Shizuoka	669,142	303	(42)	198	(51)	754	(110)	774	(83)	2,499,435
36	Yamaguchi	679,129	308	(43)	204	(52)	977	(143)	1,010	(109)	970,198
37	Aichi	690,470	313	(43)	211	(53)	664	(97)	692	(74)	4,426,496
38	Yamanashi	694,972	315	(44)	214	(53)	897	(131)	939	(101)	648,392
39	Saga	696,479	316	(44)	215	(53)	1,036	(152)	1,086	(117)	572,479
40	Saitama	717,539	325	(45)	228	(54)	661	(97)	703	(75)	3,489,822
41	Okinawa	721,361	327	(45)	230	(54)	785	(115)	838	(90)	756,000
42	Kyoto	748,431	339	(47)	248	(56)	740	(108)	807	(87)	1,290,301
43	Hyogo	781,183	354	(49)	271	(58)	916	(134)	1,022	(111)	2,729,149
44	Shiga	873,698	396	(55)	339	(65)	1,394	(204)	1,659	(185)	815,800
45	Kanagawa	909,046	412	(57)	367	(68)	690	(101)	841	(95)	3,742,918
46	Tokyo	1,193,086	541	(75)	634	(102)	982	(144)	1,420	(187)	4,651,077
47	Osaka	1,308,161	593	(82)	763	(122)	1,253	(183)	1,927	(269)	3,753,459
	Country-wide Total Pigouvian Tax		21,813,561,058 ($22 billion)		16,331,894,527 ($16 billion)		51,282,430,813 ($51 billion)		55,232,700,924 ($ 55 billion)		71,775,315

Notes: Standard errors are in the parentheses. External accident costs of marginal driver and their standard errors are calculated as follows:

Model (a): external cost = $\hat{c_2}D$, $s.e.(\hat{c_2}D) = \sqrt{var(\hat{c_2}D)} = D \times s.e.(\hat{c_2})$.

Model (b): external cost = $\hat{c_2}D + 2\hat{c_3}D^2$, (see EK, equation (3) and (4) in page 938 for derivation) $s.e.(\hat{c_2}D + 2\hat{c_3}D^2) = \sqrt{D^2 var(\hat{c_2}) + 4D^4 var(\hat{c_3}) + 2 \times 2D^3 cov(\hat{c_2}, \hat{c_3})}$.

Model (c): external cost = $\hat{c_2}D \times (\frac{M}{N})$. (= $\hat{c_2}D$ describes the marginal cost per mile of driving and $(\frac{M}{N})$ denotes that the average person is assumed to drive $\frac{M}{N}$ miles per year.) $s.e.(\hat{c_2}\frac{M}{N}D) = s.e.(\hat{c_2})(\frac{M}{N})D$.

Model (d): external cost = $(\hat{c_2}D + 2\hat{c_3}D^2) \times (\frac{M}{N})$ (First term denotes marginal externality per mile driven. Second term comes from the assumption that average person drives $\frac{M}{N}$ miles per year.) $s.e.((\hat{c_2}D + 2\hat{c_3}D^2) \times \frac{M}{N}) = \sqrt{var((\hat{c_2}D + 2\hat{c_3}D^2) \times \frac{M}{N})} = \sqrt{D^2(\frac{M}{N})^2 var(\hat{c_2}) + 4D^4(\frac{M}{N})^2 var(\hat{c_3}) + 4D^3(\frac{M}{N})^2 cov(\hat{c_2}, \hat{c_3})}$.

Table 4: External Accident Cost of Marginal Driver for Selected Prefectures

Prefecture	Traffic Density (1996)	Insurance Cost per Vehicle Model: Linear Model (a) EK's Model (3) in Table 2 $/driver	s.e.	Insurance Cost per Vehicle Model: Quadratic Model (b) EK's Model (7) in Table 3 $/driver	s.e.	Insurance Cost per Vehicle Mile Model: Linear Model (c) no corresponding model $/driver	s.e.	Insurance Cost per Vehicle Mile Model: Quadratic Model (d) EK's Model (10) in Table 3 $/driver	s.e.
Low Density									
Hokkaido	309,730	140	(19)	42	(29)	398	(58)	294	(49)
Iwate	341,378	155	(21)	51	(32)	530	(77)	404	(63)
Akita	351,565	159	(22)	54	(32)	458	(67)	353	(54)
Moderate Density									
Kumamoto	465,125	211	(29)	95	(40)	570	(83)	492	(62)
Tokushima	473,780	215	(30)	99	(40)	584	(85)	508	(63)
Niigata	488,511	222	(31)	105	(41)	667	(98)	588	(72)
High Density									
Fukuoka	665,862	302	(42)	196	(51)	671	(98)	687	(74)
Shizuoka	669,142	303	(42)	198	(51)	754	(110)	774	(83)
Yamaguchi	679,129	308	(43)	204	(52)	977	(143)	1,010	(109)
Extremely High Density									
Kanagawa	909,046	412	(57)	367	(68)	690	(101)	841	(95)
Tokyo	1,193,086	541	(75)	634	(102)	982	(144)	1,420	(187)
Osaka	1,308,161	593	(82)	763	(122)	1,253	(183)	1,927	(269)

Note: This table presents the selected prefectures from Table 3.

Table 5: Vehicle Mile Traveled: International Comparison

	the U.S.	Canada	Australia	Germany	UK	Sweden	Netherlands	Japan
(A) Number of Registered Cars (in thousand cars)	220,681	17,775	12,451	48,127	28,914 ('01)	4,429	7,847	72,393
(B) Total Vehicle Mile Traveled (million mile)	2,787,687 ('01)	193,875	119,063	367,563	287,000 ('97)	41,750 ('98)	78,125 ('00)	494,250 ('01)
(B) / (A)	12.63	10.91	9.56	7.64	9.93	9.43	9.96	6.83

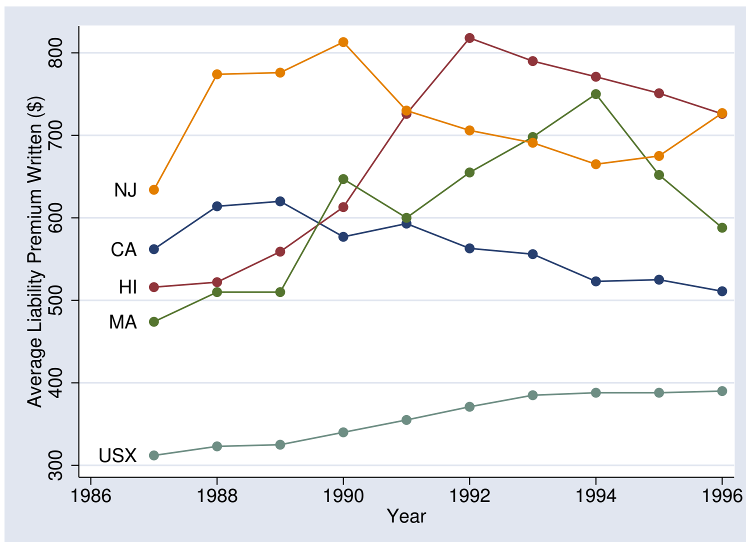
Source: Created from Table 2 in "Kotsu-jiko Tokei Nenpo"
Notes: Figures are in 2002, except for those mentioned in the parentheses. The number of registered vehicle is that of four-wheel cars.

Table 6: Traffic Accident in Japan and the U.S.

	US		Japan	
Year	2002		2002	
Number of Victims Killed	42,815		9,575	
Number of Victims Injured	3,033,000		1,166,606	
Status of Victims Killed				
Pedestrian	4,808	(11.2)	2,784	(29.1)
Bike	662	(1.5)	1,305	(13.6)
Motor Cycle	3,244	(7.6)	1,721	(18.0)
Vehicle	20,416	(47.7)	2,562	(26.8)
Other	13,446	(31.4)	1,203	(12.6)
Unknown	239	(0.6)	0	(0.0)
Population (thousand people)	288,369		127,435	
Total Lane Mile (mile)	3,967,333		728,183	
Total Vehicle-Mile Traveled (billion mile)	2,772		4,915	

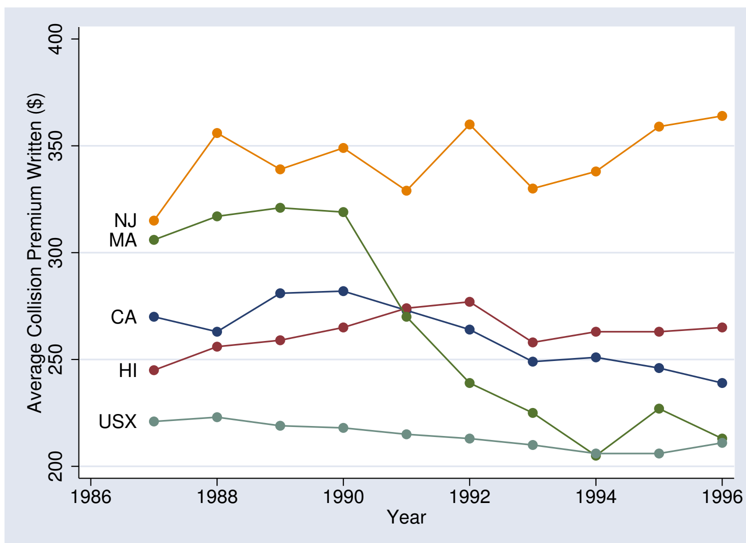
Source: "Kotsu-Jiko Tokei Nenpo" (Traffic Accident Statistics Annual).
Notes: Number of victims killed is those who were killed within 30 days. Japanese data on total lane mile data and total vehicle-mile traveled are in 2001. U.S. data on total vehicle mile traveled data is in 2001.

Figure 1: Average Auto Insurance Premium (Liability Insurance): 1987-1996



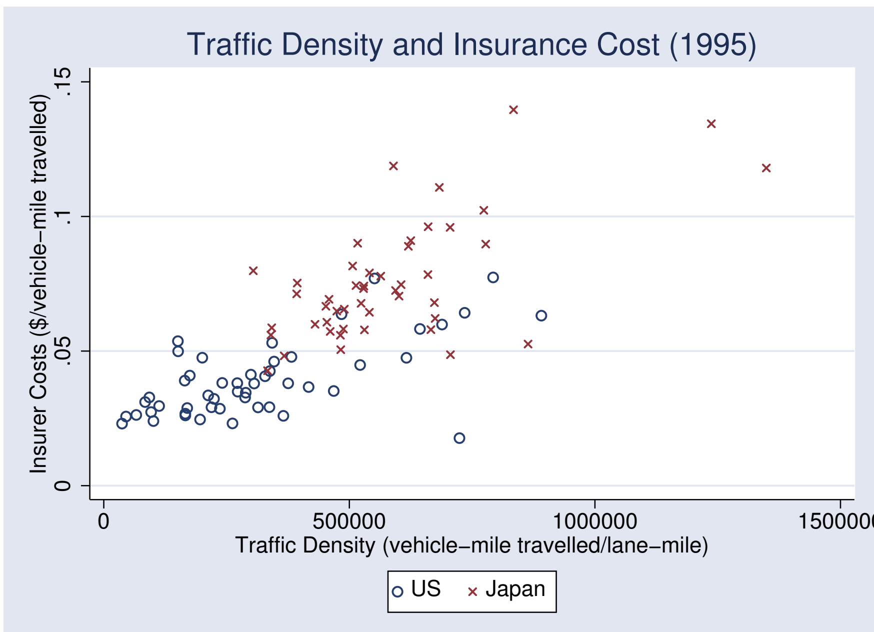
Source: National Association of Insurance Commissioners "State Average Expenditures and Premiums for Personal Automobile Insurance" (various years) Table 7.
Notes: "USX" is the U.S. average excluding CA, HI, MA, and NJ. Average auto insurance premium is calculated as ("Liability Premiums Written") / ("Liability Written Car-Years"). This figure displays that auto insurance premium has been considerably and systematically high in the four states. Also, it largely fluctuates over year, indicating that the effect might not be fully controlled by state dummies and year dummies.

Figure 2: Average Auto Insurance Premium (Collision Insurance): 1987-1996



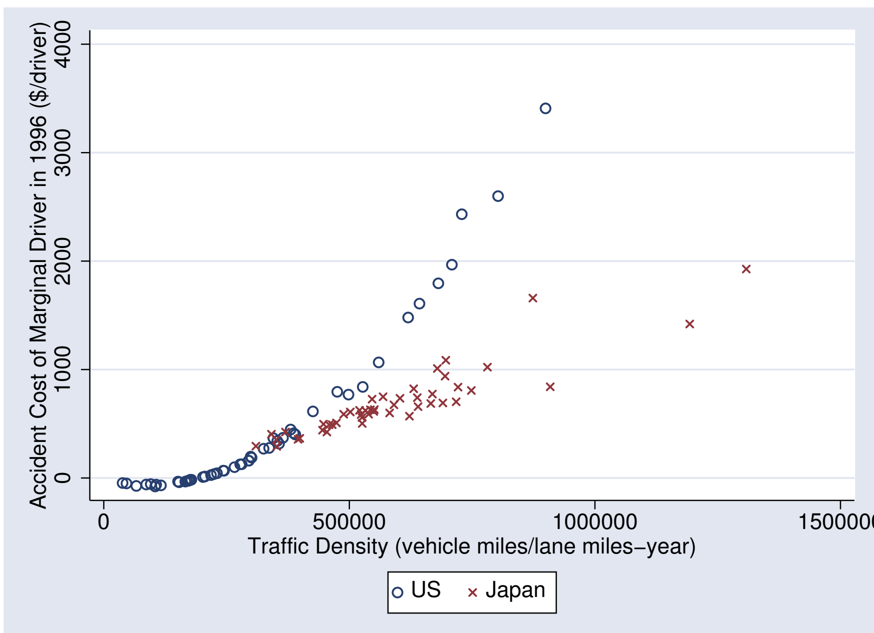
Source: National Association of Insurance Commissioners "State Average Expenditures and Premiums for Personal Automobile Insurance" (various years) Table 7.
Notes: "USX" is the U.S. average excluding CA, HI, MA, and NJ. Average auto insurance premium is calculated as ("Collision Premiums Written") / ("Collision Written Car-Years"). This figure displays that auto insurance premium has been considerably and systematically high in the four states. Also, it largely fluctuates over year, indicating that the effect might not be fully controlled by state dummies and year dummies.

Figure 3: Traffic Density and Insurance Cost (1995)



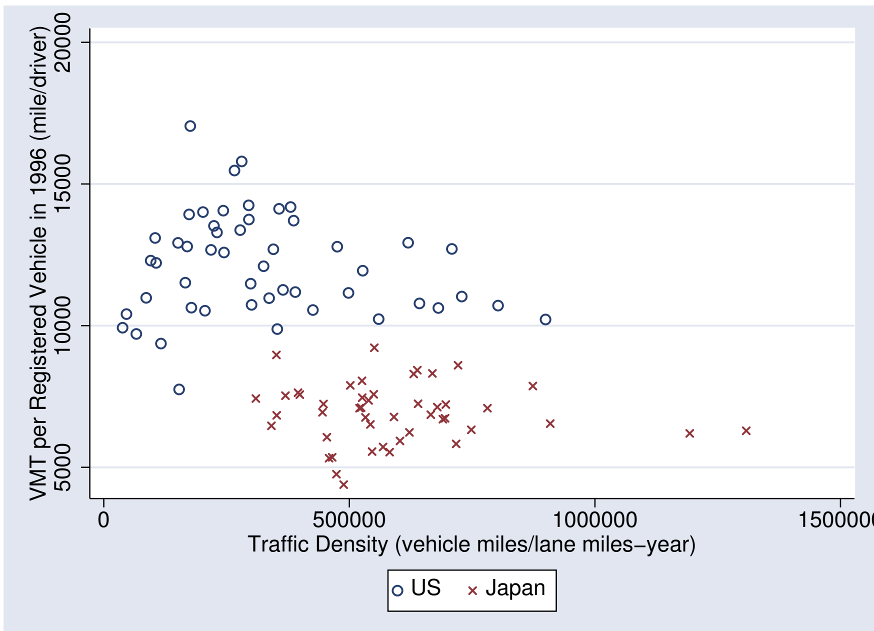
Notes: Insurance cost is in 1996 dollars. Somehow, our graph is slightly different from that in Edlin and Karaca-Mandic (2006), especially California.

Figure 4: Measured Accident Externality per Vehicle (1996)



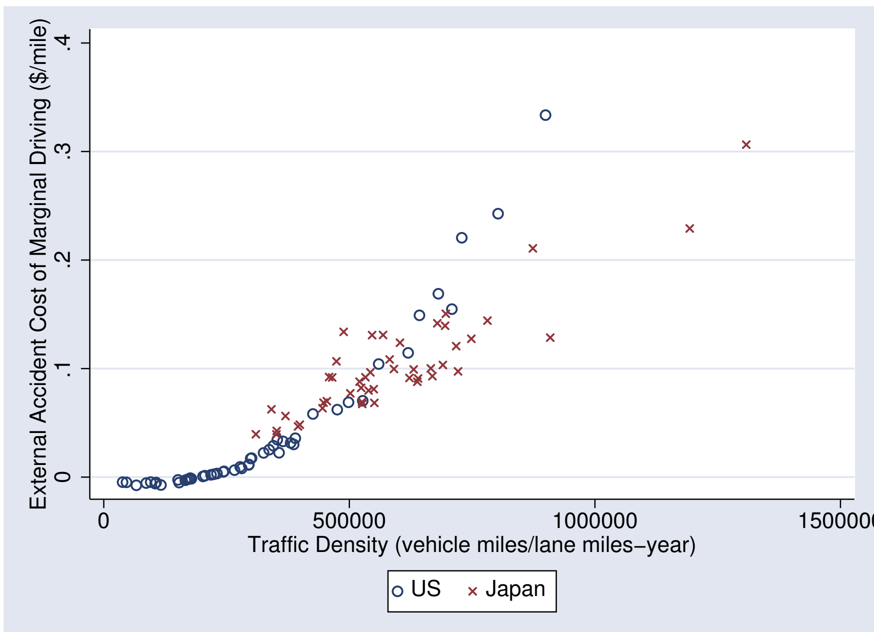
Notes: The accident externality is based on the quadratic insurer costs model, specification (10) in Table 4 of Edlin and Karaca-Mandic (2006), and model (d) in our study. Accident externality is computed as $(\hat{c}_2 D + \hat{c}_3 D^2) \times (\frac{M}{N})$. In creating the figure, we referred to Table 4 in Edlin and Karaca-Mandic (2003) which provides estimated accident externality for all states.

Figure 5: Vehicle Mile Traveled per Registered Vehicle (1996)



Source: The number of registered cars comes from *"Jido-sya Hoyu Sharyo Su"* (Japan), and from *"Highway Statistics"* Table MV-1. (the U.S.)
Notes: This figure displays the average vehicle mile traveled per registered vehicle $\left(\frac{M}{N}\right)$ in Japan and the U.S. On average, the U.S. drivers travel 1.75 times as much as Japanese drivers, suggesting that an additional driver on the road might create different accident externalities per vehicle.

Figure 6: Measured Accident Externality per Mile of Driving (1996)



Notes: This figure displays the accident externality per mile of driving, which is defined as $(N-1)\frac{dr}{dM}$. More specifically, the accident externality per mile of driving is calculated by multiplying the yearly external accident cost of marginal driver $(\hat{c_2}D + 2\hat{c_3}D^2) \times (\frac{M}{N})$ (model (d) in our study and Table 4 of Edlin and Karaca-Mandic (2003)) by $\left(\frac{N}{M}\right)$, where N is defined as the number of registered cars. The data on the number of registered cars come from *"Jido-sya Hoyu Sharyo Su"* (Japan), and from *"Highway Statistics"* Table MV-1 (the U.S.).
Interestingly, the results from Japan and the U.S. are quite similar to each other at least in the regions where the traffic density is from around 400,000 to 700,000. This finding is in sharp contrast with the results from per-vehicle analysis. The disparity between two countries, however, becomes larger in the regions where the number of observations is small.