How Risky is Distracted Driving?

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Abstract

We use data on fatal crashes to quantify the risk of distracted driving. We repurpose, extend, and improve a methodology used to estimate the riskiness of drinking drivers (Levitt and Porter, 2001). Our analysis suggests that distracted drivers are three times more likely to cause a fatal crash than focused drivers. We also estimate that distracted drivers represent three to four percent of drivers on the road at any given time. Further, we find that distractions associated with cellphone use are less likely to cause a fatal crash than are distractions from other sources. The externality costs between $.03 and $.07 per mile driven. The insurance surcharge for a distracted driving citation that could internalize the avoidable insurance losses is approximately $424 per year. Our work extends the literature on distracted driving and traffic fatalities. We believe our results can inform policymakers on the traffic-safety and economic consequences of distracted driving.

Introduction

Each year in the U.S., vehicle crashes result in thousands of fatalities, millions of injuries, and substantial economic costs. Public policy debates related to traffic safety have led policymakers to enact various measures aimed at improving traffic safety, such as incentivizing or mandating vehicle safety features, enacting seatbelt laws, and prohibiting impaired driving. In recent years, the ubiquity of cellphones in society has thrust the issue of distracted driving to the forefront of policy discussions and policy actions surrounding traffic safety. Consequently, many states have enacted measures aimed at reducing distracted driving, with a particular focus on restricting the use of cellphones.[1]

Although many states have taken actions to reduce distracted driving, policymakers and researchers continue to disagree about the risk posed by distracted drivers and the cost/benefit calculus of anti-distraction measures. Proponents of policies aimed at reducing distracted driving assert that distractions pose a significant risk to individuals on the road. The fact that many states outlaw certain distractions, such as holding cell phones, suggests many policymakers believe the political, economic, and societal cost of these regulatory and legislative measures are justified. In contrast, detractors of distracted driving mitigation measures argue that cellphone bans (and similar laws) may lead to increased police scrutiny, infringement of rights, or other negative externalities that are not warranted by the risk of distracted driving. Cotter (2019) writes about one example of a regional NAACP chapter opposing such laws, unless data on race are collected during each traffic stop.

Both proponents and detractors of distracted driving laws lean on the academic literature to support their policy positions. Proponents reference the studies that suggest distracted driving is associated with significant negative consequences that can, to a degree, be remedied by policy action. For example, Redelmeier and Tibshirani (1997) and McEvoy et al. (2006) provide evidence that the hand-held

[1] By the end of 2019, 20 states had bans on hand-held devices while driving. The laws passed in response to distracted driving are largely aimed at limiting or prohibiting the hand-held use of a cellphone while driving. The laws vary as to whether the offense is a primary offense (can be pulled over for using a device) or secondary offense (citation can be issued if stopped for another offense) as well as if the law applies to all drivers or to a sub-population of drivers (e.g. drivers under 18).

use of a cellphone while driving increases the risk of an automobile crash by a factor of four. Other researchers, using various data sources and study designs, provide additional evidence that the use of a cellphone while driving increases the likelihood of crashing (e.g., McCartt, Hellinga, and Braitman, 2006; Klauer, et al., 2006; Klauer et al., 2014). Other studies provide evidence that legislation (e.g., hand-held cellphone bans) reduces cellphone use, crashes, and automobile insurance claims (e.g., Kolko, 2009; Nikolaev et al., 2010; Sampaio et al., 2010; Braitman and McCartt, 2010; McCartt et al., 2010; Anyanwu, 2012; French and Gumus, 2018; Karl and Nyce, 2019; Karl and Nyce, 2020).

Although several studies indicate there is risk associated with distracted driving, there is not a clear consensus in the literature. McCartt et al.'s (2015) comprehensive literature review indicates that several studies find no effect of distracted driving or laws intended to limit distracted driving (Trempel et al., 2011; Bhargava and Pathania, 2013). This lack of consensus in the literature is likely caused by several empirical challenges. First among such challenges is data integrity. McCartt et al. (2015) note that "…there is considerable unsettled evidence with regard to the patterns of drivers' phone use or the effects of use on crash risk. Evaluations of cellphone and texting bans also must grapple with substantial methodological and data-related challenges that many of the reviewed studies were unable to overcome."

Reliable, uniform data on the effects of distracted driving on crash risk are scarce. Sampling cellphone records, observing drivers while operating a vehicle, and examining aggregate data pertaining to cellphone use and crashes are all methods that have been incorporated and, consequently, estimates of the risk of distracted driving vary widely across studies using different data. The low end of the estimates in prior studies suggest distracted driving could be 3 times riskier and the high end of the estimates suggest distracted driving could be 23 times riskier.

Even putting aside data and methodological issues, other concerns arise when attempting to evaluate the risk distractions pose to drivers. For example, issues pertaining to enforcement present a challenge of assessing the risk of distracted driving, as it is much easier to prove an individual was, for example, drinking and driving (e.g. employing a breathalyzer or blood test) than it is to prove that a driver was not paying attention at a specific time on the road.[2] Another problem of assessing the risk of distracted driving is that there are many forms of driving distractions (e.g. eating, adjusting radio/infotainment settings, talking to passengers, talking/texting or using other features of smart phones, etc.) that must be considered.

Given that the conflicting results in the literature represent a serious challenge for making informed policy decisions, we develop a new method for estimating the risk associated with distracted driving that overcomes several of the challenges that hinder previous studies. We draw on the work of Levitt and Porter (2001) (henceforth L&P), who develop an elegant and novel strategy for estimating the risk of drinking and driving using only data on fatal crashes. More specifically, leveraging the fact that many fatal crashes involve multiple drivers, L&P show that, for two car crashes, the relative frequency of crashes involving sober drivers and drinking drivers provides sufficient information for estimating the risk associated with drinking and driving. With this novel method, L&P use the information reported in the Fatality Analysis Reporting System (FARS) database to identify crashes involving sober and drinking drivers and they estimate that drivers that are legally drunk pose a crash risk that is 13 times greater than that of sober drivers. In this way, L&P significantly improve on the work (and shortcomings) of prior studies and provide one of the most complete and reliable insights into the risk of drinking and driving.

We apply the work of L&P as a kernel for developing a radically different strategy for estimating the risk associated with distracted driving. Our approach leverages the uniform and detailed data reported in FARS and analyzes it in a manner that allows us to 1) compare our results to the original L&P estimates of the riskiness of drinking and driving, and then apply the method to distracted driving; and 2) compare the risk of various distractions; and 3) estimate the externalities and associated economic costs of each source. In this way, our study provides insight into the risk of distracted driving that informs policy decisions.

[2] If a person drives drunk, they are generally drunk for the duration of the trip. In contrast, an individual's level of distraction can change drastically during the same duration trip, meaning that it is much easier to prove an individual is drunk at the time of a crash than distracted.

Our analysis suggests that distracted drivers represent between 3.5 and 4 percent of all drivers (at any time on the road) and are between 2.5 and 3.14 times more risky than focused drivers. Though these numbers are not as high as the relative riskiness of drinking drivers (7.76 to 8.56 times riskier in the 20:00 – 5:00 window) they are consistent with a clear and substantial risk posed by distracted driving that warrants attention from policymakers. We also find that, although the fatal crash risk of drivers who are distracted by cellphones is less than that of drivers who are distracted by other distractions, it is still greater than that of focused drivers. Results also suggest that around 23 percent to 35 percent of all distracted drivers are distracted by cellphones. We note also that estimates of relative riskiness in this analysis are likely lower-bound estimates, as the FARS reports necessarily misclassify some distracted drivers as focused due to the difficulties in proving a driver was distracted before a fatal crash occurred.

Policymakers appear to share a consensus that drunk driving poses significant traffic safety risks. As evidence, it is illegal to operate a motor vehicle with a blood alcohol content (BAC) above .08 percent (NHTSA DOT HS 811 456; 2011) in every U.S. jurisdiction. In contrast, no clear consensus exists among policymakers regarding the marginal costs of distracted driving, which likely explains the disjointed and non-uniform efforts individual states have taken to address distracted driving. We believe that our study, which more accurately and thoroughly quantifies the risk associated with distracted driving, represents an important first step toward reaching a consensus among policymakers regarding the dangers of distracted driving. In this way, we believe our work substantially informs policymakers' decisions about addressing the consequences of distracted driving.

2. The Model

L&P develop a methodology that measures the prevalence of drinking drivers on the road and the risk they pose relative to other drivers. Their methodology relies on a few assumptions and the binomial distribution to estimate both the relative risk posed by drinking drivers and the frequency of drinking and driving. Using the FARS data on two-car fatal crashes they estimate that drivers with alcohol in their blood were seven times more likely to cause a fatal crash and legally drunk drivers were thirteen times more likely. They also estimate that at peak drinking and driving times (weekends between 1:00 AM and 3:00 AM), up to 25 percent of drivers on the road have been drinking. They estimated that fines for drunk driving should be around $8,000 to internalize the cost of the externalities associated with drinking drivers.

The novel approach taken by L&P enabled them to make a limited number of assumptions and yet estimate both the frequency and relative riskiness of drunk driving from the fatal two-car crash data in the FARS dataset. L&P make five assumptions:[3]

1) There are only two types of drivers: drinking or sober;
2) There is equal mixing of drinking and sober drivers on the road:
   a) The number of interactions that a driver has with other cars is independent of driver type;
   b) Driver type does not affect the composition of the driver types with which that driver interacts;
3) A fatal crash results from a single driver's error;
4) The composition of driver types in one fatal crash is independent of the composition of driver types in other fatal crashes; and
5) Drinking (weakly) increases the likelihood that a driver makes an error resulting in a fatal crash.

[3] L&P provide a detailed discussion of how relaxing these assumptions affects their model and estimates.

These five assumptions along with properties of the binomial distribution involved with two-car fatal crashes allow L&P to estimate a measure of relative riskiness without having to assume frequency (and vice versa). This is especially appealing in the context of distracted driving, where estimates of the frequency of distracted driving vary widely by source.

Unfortunately, L&P's methodology is not a turnkey solution for measuring the risk of distracted driving. They solve for the relative riskiness of drinking drivers solely based on the observed distribution of fatal crashes. Then they back out the value of the relative exposure. One restriction of their method is that to generate a meaningful estimate of the relative riskiness, it requires a high enough percentage of the two-car fatal crashes to involve one drinking driver and one sober driver. This is not a binding constraint in their context because more than half of all drivers that cause a fatal crash have been drinking. However, our data show only about 4 percent of at-fault drivers in fatal crashes are distracted. Our method avoids this constraint by including one-, two-, and three-car crashes in the analysis to increase the number of observations. We also use a nonlinear programming (NLP) procedure to estimate the relative riskiness and relative exposure of distracted drivers by directly maximizing the log likelihood function. L&P solve a quadratic equation, which requires a minimum number of observations to estimate the relative riskiness.

2.1 Model Assumptions

Our model requires assumptions very similar to those of L&P. We make the following assumptions:

1. There are two types of drivers, distracted (D) and focused (F).
2. There is equal mixing of distracted and focused drivers on the road, meaning
    a. The number of interactions that a driver has with other cars is independent of the driver's type.
    b. A driver's type does not affect the composition of the driver types with which he or she interacts.
3. A fatal car crash results from a single driver's error.

4. The composition of driver type(s) in one fatal crash is independent of the composition of driver type(s) in other fatal crashes.
5. The relative likelihood of a distracted driver causing a one-car fatal crash is equal to the relative likelihoods of a distracted driver causing a two- or three-car fatal crash.

The first four assumptions are the same as those of L&P. However, our approach does not require the underlying behavior (distracted driving) to be riskier than focused driving, because we do not use the quadratic formula to solve the likelihood function. Our fifth assumption is necessary due to the lower frequency of distracted/focused two-car fatal crashes.

Another restriction L&P's method is that it cannot identify the parameters of the model using only one-car crashes. They must estimate the relative riskiness from the two-car crashes, back out the relative exposure, and then use the relative exposure to estimate the relative riskiness for one-car crashes. Again, because there is a high enough percentage of two-car crashes involving drinking drivers, this constraint is not binding for their study. However, in our distracted-driving analysis, the frequency of two-car fatal crashes involving at least one distracted driver is sparse in a given time and place, especially when we relax Assumption 2 and shrink the geographic and temporal units of observation. Therefore, to include as much information in the estimation as possible, our model combines one-car, two-car, and three-car fatal crashes,[4] and estimates the relative riskiness and relative exposure in one step. This necessitates our new Assumption 5 for the relative riskiness of distracted drivers. Note that Assumption 5 does not require the *probabilities* of a distracted driver causing a one-, two-, or three-car fatal crash to be equal, only that the levels of *relative* riskiness are the same.[5] Indeed, L&P's results support this assumption. There is virtually no difference between the relative likelihoods of causing one- and two-car crashes in the case of drinking or drunk drivers (Loughran and Seabury (2007)).

[4] Fatal crashes that involve more than three cars represent less than 1% of all the crashes in our data.
[5] More details are provided below in the description of the model.

2.2 Developing the Model

In a given geographic area and time period, there are, on average, N_D distracted drivers and N_F focused drivers on the road at any instant. During each instance, on average, p of all the drivers on the road experience interactions with one other car ($I_2 = 1$), during which a two-car crash is possible. Meanwhile, q of all the drivers on the road experience interactions with two other cars ($I_3 = 1$), during which a fatal crash involving three cars can happen. Therefore, $1 - p - q$ of all drivers on the road do not encounter any other cars, hence only one-car fatal crashes can occur. Thus, at any instant, for any driver on the road, the probability that the driver is of type i and does not interact with any other drivers, conditional on driving on the road ($Dr = 1$), is

$$\Pr(i, I_2 = 0, I_3 = 0 | Dr = 1) = \frac{N_i}{N_D + N_F}(1 - p - q). \quad (1)$$

The respective joint distributions for the driver encountering one or two other cars with a pair of driver types, conditional on driving on the road, are

$$\Pr(ij, I_2 = 1 | Dr = 1) = \frac{N_i N_j}{(N_D + N_F)^2} p, \quad (2)$$

$$\Pr(ijk, I_3 = 1 | Dr = 1) = \frac{N_i N_j N_k}{(N_D + N_F)^3} q. \quad (3)$$

Let θ_i be the probability that a driver of type i causes a fatal one-car crash. Assumption 5 implies that the probability that a driver of type i causes a two-car or three-car fatal crash is proportional to that of causing a one-car fatal crash. Define δ and λ as scaling parameters so that a driver of type i has probabilities of $\delta\theta_i$ and $\lambda\theta_i$ to cause a two-car and a three-car fatal crash, respectively. Assumption 3 implies that the joint probabilities of driver type(s) and a fatal crash ($A = 1$),[6] conditional on driving on the road are

$$\Pr(i, I_2 = 0, I_3 = 0, A = 1 | Dr = 1) = \frac{N_i \theta_i}{N_D + N_F}(1 - p - q), \quad (4)$$

[6] L&P call crashes "accidents" and label them A in their model. We use the more descriptive term "crash" in this paper, yet we retain the label A in the model for ease of comparison to L&P.

$$\Pr(ij, I_2 = 1, A = 1 | Dr = 1) = \frac{N_i N_j \delta(\theta_i + \theta_j)}{(N_D + N_F)^2} p, \tag{5}$$

$$\Pr(ijk, I_3 = 1, A = 1 | Dr = 1) = \frac{N_i N_j N_k \lambda\left(\theta_i + \theta_j + \theta_k\right)}{(N_D + N_F)^3} q. \tag{6}$$

The probabilities of driver type(s) conditional on the occurrence of a fatal crash can now be calculated from equations (4) – (6):

$$\Pr(i, I_2 = 0, I_3 = 0 | A = 1) = \frac{\Pr(i, I_2 = 0, I_3 = 0, A = 1 | Dr = 1)}{\Pr(A = 1 | Dr = 1)}$$
$$= \frac{\Pr(i, I_2 = 0, I_3 = 0, A = 1 | Dr = 1)}{\Pr(I_2 = 0, I_3 = 0, A = 1 | Dr = 1) + \Pr(I_2 = 1, A = 1 | Dr = 1) + \Pr(I_3 = 1, A = 1 | Dr = 1)}$$
$$= \frac{(N_D + N_F)^2 N_i \theta_i (1 - p - q)}{(N_D + N_F)^2 (N_D \theta_D + N_F \theta_F)[(1 - p - q) + 2p\delta + 3q\lambda]}, \tag{7}$$

$$\Pr(ij, I_2 = 1 | A = 1) = \frac{(N_D + N_F) N_i N_j \delta(\theta_i + \theta_j) p}{(N_D + N_F)^2 (N_D \theta_D + N_F \theta_F)[(1 - p - q) + 2p\delta + 3q\lambda]}, \tag{8}$$

$$\Pr(ijk, I_3 = 1 | A = 1) = \frac{N_i N_j N_k \lambda\left(\theta_i + \theta_j + \theta_k\right) q}{(N_D + N_F)^2 (N_D \theta_D + N_F \theta_F)[(1 - p - q) + 2p\delta + 3q\lambda]}. \tag{9}$$

Denote P_i, P_{ij}, and P_{ijk} as the probabilities that the composition of driver type(s) is (are) of type i, types i and j, and types i, j, and k, respectively, given that a fatal crash occurs. Define $\theta = \theta_D / \theta_F$ and $N = N_D / N_F$, where θ is the relative likelihood that a distracted driver will cause a fatal crash compared to a focused driver, and N is the average ratio of distracted drivers to focused drivers on the road at any instant in a particular geographic area and period. We can now explicitly state the probabilities in terms of θ and N as:

$$P_D = \frac{(N + 1)^2 N\theta(1 - p - q)}{(N + 1)^2 (N\theta + 1)[(1 - p - q) + 2p\delta + 3q\lambda]}, \tag{10}$$

$$P_F = \frac{(N + 1)^2 (1 - p - q)}{(N + 1)^2 (N\theta + 1)[(1 - p - q) + 2p\delta + 3q\lambda]}, \tag{11}$$

$$P_{DD} = \frac{2(N + 1) N^2 \theta \delta p}{(N + 1)^2 (N\theta + 1)[(1 - p - q) + 2p\delta + 3q\lambda]}, \tag{12}$$

$$
\begin{aligned}
P_{DF} &= \Pr(i = D, j = F, I_2 = 1 | A = 1) + \Pr(i = F, j = D, I_2 = 1 | A = 1) \\
&= \frac{2(N+1)N(\theta+1)\delta p}{(N+1)^2(N\theta+1)[(1-p-q)+2p\delta+3q\lambda]},
\end{aligned} \tag{13}
$$

$$
P_{FF} = \frac{2(N+1)\delta p}{(N+1)^2(N\theta+1)[(1-p-q)+2p\delta+3q\lambda]}, \tag{14}
$$

$$
P_{DDD} = \frac{3N^3\theta\lambda q}{(N+1)^2(N\theta+1)[(1-p-q)+2p\delta+3q\lambda]}, \tag{15}
$$

$$
\begin{aligned}
P_{DDF} &= \Pr(i = D, j = D, k = F, I_3 = 1 | A = 1) \\
&+ \Pr(i = D, j = F, k = D, I_3 = 1 | A = 1) + \Pr(i = F, j = D, k = D, I_3 = 1 | A = 1) \\
&= \frac{3N^2(2\theta+1)\lambda q}{(N+1)^2(N\theta+1)[(1-p-q)+2p\delta+3q\lambda]},
\end{aligned} \tag{16}
$$

$$
\begin{aligned}
P_{DFF} &= \Pr(i = D, j = F, k = F, I_3 = 1 | A = 1) \\
&+ \Pr(i = F, j = D, k = F, I_3 = 1 | A = 1) + \Pr(i = F, j = F, k = D, I_3 = 1 | A = 1) \\
&= \frac{3N(\theta+2)\lambda q}{(N+1)^2(N\theta+1)[(1-p-q)+2p\delta+3q\lambda]},
\end{aligned} \tag{17}
$$

$$
P_{FFF} = \frac{3\lambda q}{(N+1)^2(N\theta+1)[(1-p-q)+2p\delta+3q\lambda]}. \tag{18}
$$

Because Assumption 4 ensures the independence of the composition of driver type(s) in a fatal crash, the joint distribution of driver type(s) involved in fatal crashes is given by the multinomial distribution. Let A_i, A_{ij}, and A_{ijk} be the numbers of fatal crashes involving driver(s) of type i, types i and j, and types i, j, and k, respectively, and denote A_{total} as the total number of fatal crashes, we can derive the likelihood function as:

$$
\begin{aligned}
&\Pr(A_D, A_F, A_{DD}, A_{DF}, A_{FF}, A_{DDD}, A_{DDF}, A_{DFF}, A_{FFF} | A_{total}) \\
&= \frac{(A_D + A_F + A_{DD} + A_{DF} + A_{FF} + A_{DDD} + A_{DDF} + A_{DFF} + A_{FFF})!}{A_D!\, A_F!\, A_{DD}!\, A_{DF}!\, A_{FF}!\, A_{DDD}!\, A_{DDF}!\, A_{DFF}!\, A_{FFF}!} \\
&* (P_D)^{A_D}(P_F)^{A_F}(P_{DD})^{A_{DD}}(P_{DF})^{A_{DF}}(P_{FF})^{A_{FF}}(P_{DDD})^{A_{DDD}}(P_{DDF})^{A_{DDF}}(P_{DFF})^{A_{DFF}}(P_{FFF})^{A_{FFF}}.
\end{aligned} \tag{19}
$$

In the empirical analysis, we substitute equations (10) – (18) into equation (19) and estimate the values of θ and N by maximizing the log likelihood function, or the log function of equation (19). The first-order condition of equation (19) yields the maximum likelihood estimation of the probabilities:

$$
\begin{aligned}
&\hat{P}_D = \frac{A_D}{A_{total}}, \hat{P}_F = \frac{A_F}{A_{total}}, \hat{P}_{DD} = \frac{A_{DD}}{A_{total}}, \hat{P}_{DF} = \frac{A_{DF}}{A_{total}}, \hat{P}_{FF} = \frac{A_{FF}}{A_{total}}, \\
&\hat{P}_{DDD} = \frac{A_{DDD}}{A_{total}}, \hat{P}_{DDF} = \frac{A_{DDF}}{A_{total}}, \hat{P}_{DFF} = \frac{A_{DFF}}{A_{total}}, \hat{P}_{FFF} = \frac{A_{FFF}}{A_{total}}.
\end{aligned} \tag{20}
$$

From equation (20) and the maximization of equation (19) we can obtain the following expressions of our model's parameters:

$$\frac{N_D\theta_D[(1-p-q)+2\delta p+3\lambda q]}{N_F\theta_F[(1-p-q)+2\delta p+3\lambda q]}=N\theta$$
$$=\frac{\left[A_{DDF}\left(\frac{2\theta}{2\theta+1}\right)+A_{DFF}\left(\frac{\theta}{\theta+2}\right)+A_{DF}\left(\frac{\theta}{\theta+1}\right)+A_{DDD}+A_{DD}+A_D\right]}{\left[A_{DDF}\left(\frac{1}{2\theta+1}\right)+A_{DFF}\left(\frac{2}{\theta+2}\right)+A_{DF}\left(\frac{1}{\theta+1}\right)+A_{FFF}+A_{FF}+A_F\right]}, \qquad (21)$$

$$\frac{(1-p-q)(N_D\theta_D+N_F\theta_F)}{[(1-p-q)+2\delta p+3\lambda q](N_D\theta_D+N_F\theta_F)}=\frac{1-p-q}{(1-p-q)+2\delta p+3\lambda q}$$
$$=\frac{A_D+A_F}{A_{total}}, \qquad (22)$$

$$\frac{2p\delta}{(1-p-q)+2\delta p+3\lambda q}=\frac{A_{DD}+A_{DF}+A_{FF}}{A_{total}}, \qquad (23)$$

$$\frac{3q\lambda}{(1-p-q)+2\delta p+3\lambda q}=\frac{A_{DDD}+A_{DDF}+A_{DFF}+A_{FFF}}{A_{total}}. \qquad (24)$$

Equation (21) expresses the ratio of fatal crashes caused by distracted drivers over those caused by focused drivers in terms of θ and the observed numbers of fatal crashes. Expressed in the same terms, equations (22) – (24) represent the ratios of single-car, two-car, and three-car fatal crashes over the total number of fatal crashes, respectively.

Substituting equations (22) – (24) into equations (10) – (18) enables expressing the probabilities solely in terms of θ and the observed numbers of fatal crashes. Substituting these probabilities into equation (19) yields the corresponding expression of the likelihood function. Recall that L&P need a high enough percentage of drinking-sober crashes in two-car fatal crashes to generate a meaningful estimate. They do point out in their paper that in the cases when the percentage in low, the estimates of the relative riskiness are one. A potential drawback is that this method will cause downward bias in the estimation because drinking drivers should, on average, impose greater risk than sober drivers. The issue becomes much more problematic in estimates of the relative riskiness of distracted drivers, because in most of the geographic and temporal units, the percentage of distracted-focused crashes in two-car fatal crashes is well below the level required for using L&P's method.

We address this issue by using a nonlinear programming (NLP) procedure to estimate θ by directly maximizing the log likelihood function (the log function of equation (19), which is solely expressed in θ after plugging in equations (10) – (18) and equations (22) – (24)). After we obtain the respective estimates of θ for different geographic and temporal observation units, we plug these θ values back into the equations to express the log likelihood function solely in N. The implied relative exposure of distracted drivers for each geographic and temporal unit can then be estimated by maximizing the log likelihood function.

In the estimation process, as long as at least one distracted driver and at least one focused driver appear in the police reports for a particular geographic and temporal unit, we can use the information from that unit. For some smaller geographic and temporal units, there were not any three-car fatal crashes, because this type of fatal crashes is the rarest compared with one-car and two-car crashes (in some cases, there were not any two-car fatal crashes). In these cases, the respective probabilities for three-car (two-car) fatal crashes enter the log likelihood function as zeros, and do not affect the maximization process. This minimizes the downward bias of the estimation of relative riskiness.

3. Empirical Analysis

3.1 Comparison of Estimation Methods

We begin the empirical analysis by replicating L&P's analysis and comparing their results to results from their sample using our method.[7] To provide an impression of the differences between the method developed in this paper and the one from L&P, Table 1 contains a replication of the results shown in L&P Table 2 and results using the NLP method in this paper. The new method is applied to the L&P

[7] Dunn and Tefft (2020) note that L&P do not provide enough information to replicate their results. We make assumptions in data screening that produce results closest to those reported by L&P.

sample (FARS data for the period between 1983 and 1993) to offer a direct comparison of our method and L&P's method. The results are summarized in Table 1.

Table 1: Comparison of the Estimates for Relative Riskiness of Drinking Drivers to Sober Drivers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unit of observation for "equal mixing" assumption	all data	hour	hour× year	hour× year× weekend	hour× region× year	hour× region× year× weekend	hour× state× year	hour× state× year× weekend
Two-car fatal crash relativity (L&P's method)	3.79 (.14)	4.87 (.16)	4.92 (.16)	5.14 (.16)	5.35 (.17)	5.74 (.18)	6.48 (.20)	7.51 (.22)
One car fatal crash relativity (L&P's method)	5.04 (.11)	5.46 (.12)	5.50 (.12)	5.67 (.12)	5.83 (.12)	6.13 (.13)	6.72 (.14)	7.45 (.15)
Fatal crash relativity (Combined crash types, our method)	6.21 (.00)	6.02 (.30)	6.00 (.15)	6.08 (.16)	6.05 (.16)	6.14 (.15)	6.46 (.21)	6.53 (.20)
Degrees of freedom (L&P's method)	3	11	101	200	884	1,764	3,427	6,668
Degrees of freedom (Our method)	3	11	101	200	893	1,784	4,696	8,521

Note: Degrees of freedom represent the number of units of observation that contain at least one crash (plus 2). Numbers in parentheses are standard errors.

Emulating L&P, moving from column (1) through column (8) we relax the "equal mixing" assumption to include more units of observation. The first row shows the unit of observation used in both L&P and our analysis. The second and third rows show the relative riskiness of drinking drivers from L&P. The fourth row contains the combined fatal crash relativities for drinking drivers (combines one, two, & three car fatal crashes). Our analysis uses a larger sample of units than does L&P because our method can accommodate more information. The fifth and sixth rows contain the degrees of freedom in each analysis, demonstrating that our method preserves more observations in the data.

There are two main differences in the estimates. Estimates from our method are much more consistent across columns, and the downward bias issue, especially for the lower numbered columns, is much less severe. For column (8), where the geographic and temporal units are the smallest, our estimate for the relative riskiness of drinking drivers is lower than the original L&P estimates. Time-space units with “too few” fatal crashes caused by drinking drivers are dropped in L&P’s analysis, which can inflate estimates of the relative riskiness of drinking drivers. The degrees of freedom in column (8) show that our method uses almost 2,000 more geographic and temporal units than the L&P approach. Dropping these additional units will increase estimates of the relative riskiness of drinking drivers. When these geographic and temporal units are aggregated into larger units in columns (1) through (7), the actual information aggregated into these geographic and temporal units in the L&P method is still less than that of our method.[8] Therefore, our method can improve not only the downward bias issue for the lower numbered columns, but also the over-estimation issue for the upper numbered columns.[9]

3.2 Relative Riskiness and Exposure of Distracted Drivers and Drinking Drivers

Distracted driving is a much more recent phenomenon than drinking driving, thus this paper uses more recent data. Fatality Analysis Reporting System (FARS) data from 2000 to 2018 is used to estimate the relative riskiness and exposure of distracted drivers and drinking drivers. FARS records detailed information on all fatal automobile crashes that occur on public roads in the United States. Table 2 and Table 3 summarize the numbers of fatal crashes and provides means for the compositions of each type of fatal crash in the samples. The percentage of distracted drivers in all fatal crashes does not vary much between different hours, but the percentage of drinking drivers in all fatal crashes is much higher in the evening hours than in day-time hours. Therefore, to provide consistent and robust estimates, the analysis of distracted drivers uses fatal crashes from all 24 hours while the analysis of drinking drivers is limited to fatal crashes between 20:00 and 5:00.

[8] This occurs even though the differences between the numbers of the more aggregated geographic and temporal units used in the two estimations become smaller (in columns (1) to (4), these numbers are the same).
[9] More on addressing the upward bias is discussed with results in Table 7.

Table 2: Summary Statistics with Distracted Driving Details for Fatal Crashes (2000 – 2018, no time constraints)

Total number of fatal crashes	555,287
Total number of fatal one-car crashes	332,151
Total number of fatal two-car crashes	196,303
Total number of fatal three-car crashes	26,833
Percentage of distracted drivers in all fatal crashes	7.4
Percentage of fatal one-car crashes with:	
One distracted driver	9.4
One focused driver	90.6
Percentage of fatal two-car crashes with:	
Two distracted drivers	0.7
One distracted driver and one focused driver	10.9
Two focused drivers	88.4
Percentage of fatal three-car crashes with:	
Three distracted drivers	0.4
Two distracted drivers and one focused driver	1.1
One distracted driver and two focused drivers	12.5
Three focused drivers	86.1

Table 3: Summary Statistics with Drinking and Driving Details for Fatal Crashes (2000 – 2018, between 8:00 PM and 5:00 AM)

Total number of fatal crashes	205,541
Total number of fatal one-car crashes	150,758
Total number of fatal two-car crashes	49,333
Total number of fatal three-car crashes	5,450
Percentage of drinking drivers in all fatal crashes	42.5
Percentage of fatal one-car crashes with:	
One drinking driver	53.1
One sober driver	46.9
Percentage of fatal two-car crashes with:	
Two drinking drivers	6.9
One drinking driver and one sober driver	46.1
Two sober drivers	47.0
Percentage of fatal one-car crashes with:	
Three drinking drivers	0.9
Two drinking drivers and one sober driver	7.3
One drinking driver and two sober drivers	45.0
Three sober drivers	46.8

Table 2 shows that, although the total number of fatal crashes is quite large, the percentage of distracted drivers in the sample is small. Therefore, the numbers of two-car crashes between two distracted drivers and three-car crashes involving three distracted drivers are relatively small. Hence, as discussed earlier, L&P's method cannot provide a reliable estimate.[10] Table 3 shows that the sample size for drinking drivers is significantly smaller than that of distracted drivers because we only use fatal crashes between 20:00 and 5:00, but the presence of drinking drivers in fatal crashes are much more common.

Table 4 presents the maximum likelihood estimates of the relative fatal crash risks for distracted drivers (Table 5 for drinking drivers) in increasingly granular cuts of the data. As we relax the "equal mixing" assumption from column (1) to column (8), the potential downward bias of the relative riskiness estimates of distracted drivers and drinking drivers are mitigated. Again, as can be observed from the pattern moving from left to right in the table, the downward bias is very mild with our method, and the estimates across columns are very consistent. The implied fractions of distracted drivers and drinking drivers in the tables are also very consistent across columns. The consistency in our estimates suggest that our method mitigates the downward bias in the estimates of the relative riskiness, and the upward bias in the estimates of the relative exposure caused by relaxing the "equal mixing" assumption.

[10] As mentioned in L&P, "the lack of drinking-drinking crashes during the daytime period makes estimation difficult." They circumvent the problem by limiting their sample to nighttime hours. However, the numbers of fatal crashes involving multiple distracted drivers are low in all hours.

Table 4: Estimates for Relative Riskiness of Distracted Drivers (2000-2018, all hours and days)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unit of observation for “equal mixing” assumption	all data	hour	hour× year	hour× year× weekend	hour× region× year	hour× region× year× weekend	hour× state× year	hour× state× year× weekend
Relative riskiness of distracted drivers	2.49 (.00)	2.79 (.12)	2.85 (.09)	2.87 (.09)	2.91 (.11)	2.95 (.11)	3.12 (.23)	3.14 (.23)
Implied fraction of distracted drivers	.038 (.000)	.035 (.001)	.036 (.001)	.036 (.001)	. 036 (.001)	.036 (.000)	.038 (.001)	.040 (.001)
Degrees of freedom	3	26	458	913	4,016	7,280	13,138	18,177

Note: Degrees of freedom represent the number of units of observation that contain at least one crash (plus 2). Numbers in parentheses are standard errors.

The fatal crash risk of distracted drivers rises monotonically from 2.49 to 3.14 times greater than that of focused drivers and the risk of drinking drivers is about eight times greater than that of sober drivers. Overall, the results imply that at every instant, about three to four percent of drivers on the road are being distracted, while approximately ten to eleven percent of drivers on the road have been drinking (between 8 PM & 5 AM).[11] The degrees of freedom suggest that when disaggregating the data from column (7) to column (8), significant information is lost because there were many time-space units with no observations of fatal crashes involving at least one distracted driver. This probably suggests that this level of disaggregation is too refined (going from column (7) to column (8)) due to the low percentage of distracted drivers in the sample and could be the reason why the implied fraction of distracted drivers does not decrease from column (7) to column (8).

Table 5: Estimates for Relative Riskiness of Drinking Drivers (2000-2018, 8 PM to 5 AM only)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unit of observation for "equal mixing" assumption	all data	hour	hour× year	hour× year× weekend	hour× region× year	hour× region× year× weekend	hour× state× year	hour× state× year× weekend
Relative riskiness of drinking drivers	8.36 (.00)	8.11 (.39)	8.23 (.21)	8.47 (.21)	8.29 (.19)	8.56 (.20)	7.76 (.22)	8.03 (.24)
Implied fraction of drinking drivers	.113 (.000)	.109 (.016)	.108 (.004)	.103 (.003)	.105 (.002)	.100 (.002)	.105 (.002)	.100 (.002)
Degrees of freedom	3	11	173	344	1,541	3,075	7,369	12,880

Note: Degrees of freedom represent the number of units of observation that contain at least one crash (plus 2). Numbers in parentheses are standard errors.

Table 6 presents separate estimates of the relative risk of distracted drivers across the years of our sample. There is significant variation in the coefficient estimates between 2000 and 2006. The relative riskiness of distracted drivers is quite high for the years 2007 to 2009, which coincide with the introductions of the first iPhones and the 3G wireless mobile telecommunications network. The relative riskiness then declines and becomes stable between 2010 and 2018. This is not consistent with the significant increase in motor vehicle deaths in the United States in 2015 and 2016 that many have attributed to increased distracted driving.

[11] While the percentage of distracted drivers on the road at any given time is lower, there are far more drivers on the road during daylight hours than the hours when drinking and driving is more prominent.

Table 6: Estimates for Relative Riskiness of Distracted Drivers (Allowing for Risk to Vary across Years)

Year	Relative Riskiness of Distracted Drivers	Implied Fraction of Distracted Drivers	Number of Fatal Crashes involving Distracted Drivers
2000	3.78	0.028	3,472
2001	3.49	0.030	3,573
2002	1.86	0.053	3,760
2003	1.43	0.076	4,369
2004	2.31	0.045	3,768
2005	2.00	0.045	3,449
2006	2.69	0.048	4,491
2007	3.55	0.040	4,545
2008	3.82	0.043	4,641
2009	3.51	0.048	4,362
2010	2.51	0.035	2,491
2011	2.39	0.038	2,586
2012	2.81	0.016	1,331
2013	2.62	0.016	1,141
2014	2.95	0.014	1,158
2015	2.74	0.016	1,286
2016	2.75	0.031	2,615
2017	2.23	0.034	2,418
2018	2.01	0.033	2,102

Note:

Throughout the analysis, we rely on the law enforcement officers' assessment of the distracted status of involved drivers, which is a potentially under-reported due to the difficulties in identifying distracted drivers after fatal crashes. Results in Table 7 examine the sensitivity of our estimates to four scenarios of driver misclassification, with distracted drivers being 25-percent, 50-percent, 75-percent, and 100-percent more than is reported in the FARS data. If the actual number of distracted drivers is underreported, the relative riskiness of such drivers overstated, and the percentage of these drivers on the road is understated.[12] This is different from L&P, where they find that if five percent of drinking drivers are misclassified as sober, the relative riskiness increases, and the implied fraction of these drivers decreases. From the degrees of freedom used in each analysis, we can see that many more time-space units, hence much more information, is being used in the estimation as the reported percentage of distracted driver increases. Therefore, we can again verify that due to the way information and

[12] We observe similar patterns when we assume that certain percentages of drinking drivers are misclassified as sober.

observations are used (or not used) in L&P's method, they over-estimate the relative riskiness in the upper columns when the time-space units are smaller, and that our method mitigates this upward bias.

Table 7: Sensitivity of Estimates to Measurement Error

	Relative Riskiness for Distracted Drivers	Implied Fraction of Distracted Drivers	Degrees of Freedom
Baseline	3.14 (.23)	.040 (.001)	18,177
Number of Distracted Drivers is 25% Higher	2.59 (.14)	.053 (.001)	21,613
Number of Distracted Drivers is 50% Higher	2.28 (.10)	.068 (.001)	24,044
Number of Distracted Drivers is 75% Higher	2.02 (.07)	.085 (.001)	25,799
Number of Distracted Drivers is 100% Higher	1.85 (.06)	.104 (.001)	27,226

Note: Numbers in parentheses are standard errors.

Table 8 presents results for other driver traits and compares them to results for drinking drivers and distracted drivers. In general, younger drivers are about 1.6 times more likely than older drivers, and male drivers are about 1.2 times more likely than female drivers, to cause fatal crashes.

Table 8: Estimates for Relative Riskiness by other Driver Characteristics (2000-2018)

Comparison Groups	Relative Riskiness for First Category Named	Implied Fraction of Drivers in the First Category Named
Distracted Drivers vs Focused Drivers	3.14 (.23)	.040 (.001)
Drinking Drivers vs Sober Drivers	8.03 (.24)	.100 (.002)
Under Age 25 vs All Others	1.60 (.03)	.191 (.001)
Male vs Female	1.20 (.02)	.700 (.001)

Note: Numbers in parentheses are standard errors.

Table 9 reports estimates that allow for interactions between distracted driving and other risk factors such as gender and age. Doing so allows for differential fatal crash risk estimates for young and old drivers or male and female drivers who have or have not been distracted before fatal crashes. Focused drivers over the age of 25 or being females are used as respective baselines. Both age and gender have significant impacts on fatal crash risk among distracted drivers. Distracted drivers who are young or female are more than twice as likely to cause fatal crashes as distracted drivers who are old or male.

3.3 Relative Riskiness and Exposure of Distracted Drivers by Source of Distraction

Distracted driving is often thought to be a singular function of cellphone use. However, our data show that distracted driving fatalities are less likely to be associated with cellphone use than with other distractions including eating, passengers, insects and reptiles, and other electronics. This finding motivates our analysis of relative risk by source of distraction.

Table 9: Estimates of Relative Riskiness (Allowing for Interactions between Distracted Driving and Other Driver Characteristics)

Driver Category	Relative Riskiness to Baseline Category (1)	Implied Fraction of Drivers (2)
Under age 25 and distracted	6.96	.008
	(.88)	(.000)
Over age 25 and distracted	3.42	.031
	(.27)	(.001)
Under age 25 and focused	1.95	.161
	(.08)	(.001)
Over age 25 and focused	**1.00**	**.800**
Male and distracted	2.98	.039
	(.30)	(.003)
Female and distracted	6.05	.010
	(.16)	(.001)
Male and focused	.86	.702
	(.03)	(.002)
Female and focused	**1.00**	**.249**

Note: Values in column 1 are maximum likelihood estimates of the fatal crash risk of the named group relative to the named baseline group (i.e., the group with a relative risk defined to be equal to one and written in **bold** type). All specifications assume equal mixing by state×year×day×hour and therefore are comparable to column 8 of Table 4. Estimates are based on the same data sample used in Table 4. Standard errors are in parentheses.

We compare distracted driving by source of distraction in three steps. First, we estimate the risk of drivers distracted by cellphones relative to focused drivers. Second, we estimate the risk of drivers distracted by other sources relative to focused drivers. Finally, we compare the estimates of relative risk by source of distraction.

Table 10 presents summary statistics for the samples used to compare the relative risk of cellphone distraction to that of distraction from other sources. The sample for this analysis is smaller than preceding analyses because FARS only began collecting the source of distraction in 2010. The cellphone distraction sample excludes crashes involving distraction from other sources. Likewise, the other distraction sample excludes crashes involving cellphone distraction.

Table 10: Summary Statistics for Distracted Driving by Source of Distraction (2010-2018)

	Cellphone distraction sample	Other distraction sample
Total number of fatal crashes	223,499	234,818
Total number of fatal one-car crashes	136,232	142,283
Total number of fatal two -car crashes	76,927	195,114
Total number of fatal three-car crashes	10,340	11,171
Percentage of distracted drivers in all fatal crashes	0.94	4.27
Percentage of fatal one-car crashes with:		
One distracted driver	1.1	5.3
One focused driver	98.9	94.7
Percentage of fatal two-car crashes with:		
Two distracted drivers	0.1	0.2
One distracted driver and one focused driver	1.5	6.8
Two focused drivers	98.4	93.1
Percentage of fatal three-car crashes with:		
Three distracted drivers	0.05	0.09
Two distracted drivers and one focused driver	0.2	0.4
One distracted driver and two focused drivers	1.5	8.5
Three focused drivers	98.2	90.9

Notes: Other distraction indicates distraction by a source other than a cellphone. The cellphone distraction sample includes all fatal crashes involving focused drivers and drivers distracted by cellphones. Likewise, the other distraction sample excludes crashed involving drivers distracted by a cellphone.

We estimate the riskiness of and exposure to drivers distracted by cellphones relative to drivers distracted by other factors using the same technique described above. Table 11 presents the results of estimating relative risk of cellphone distraction versus focus, the relative risk of other distraction versus focus, and the ratio of cellphone distraction risk to other distraction risk.

Table 11: Estimates for Relative Riskiness of Distracted Drivers by Source of Distraction (2010-2018)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unit of observation for “equal mixing” assumption	all data	hour	hour× year	hour× year× weekend	hour× region× year	hour× region× year× weekend	hour× state× year	hour× state× year× weekend
Relative riskiness of cellphone distracted drivers	1.76 (.00)	1.95 (.13)	2.01 (.14)	2.08 (.15)	2.53 (.20)	2.73 (.23)	2.89 (.27)	3.17 (.32)
Implied fraction of cellphone distracted drivers	.0062 (.0000)	.0058 (.0002)	.0057 (.0001)	.0057 (.0001)	. 0053 (.0001)	.0057 (.0001)	.0073 (.0002)	.0080 (.0002)
Degrees of freedom for cellphone distracted drivers	3	26	217	411	1,306	1,625	1,991	2,195
Relative riskiness of other distracted drivers	2.54 (.00)	3.20 (.23)	3.34 (.20)	3.37 (.22)	3.31 (.19)	3.42 (.22)	4.33 (.35)	4.73 (.41)
Implied fraction of other distracted drivers	.021 (.000)	.018 (.001)	.018 (.001)	.018 (.001)	.018 (.000)	.018 (.000)	.014 (.000)	.015 (.000)
Degrees of freedom for other distracted drivers	3	26	218	433	1,837	3,067	5,154	6,589
Relative riskiness of cellphone distracted drivers ÷ Relative riskiness of other distracted drivers	0.69	0.61	0.60	0.62	0.76	0.80	0.67	0.67

Note: “Other distracted drivers” are drivers distracted by something other than a cellphone. The difference in relative riskiness between cellphone distractions and other distractions is statistically significant based on a two-sample T-test with unequal variances. Degrees of freedom represent the number of units of observation that contain at least one crash (plus 2). Numbers in parentheses are standard errors.

Results show that drivers who are distracted by cellphones are less risky than drivers who are distracted by other factors. This could be because drivers tend to manipulate cellphones more often in less demanding situations, and vice versa, which is consistent with the findings of Kidd et al. (2016), and more generally with Peltzman (1975). It does not, however, explain why the same behavior does not hold for other sources of distraction. Perhaps the focus on handheld devices in public policy and public education has (falsely) led drivers to believe that cellphones are the only dangerous source of distraction in vehicles.

Although drivers who are distracted by cellphones are relatively less risky than drivers who are distracted by other sources in terms of causing a fatal crash, it does not mean that they are less risky than focused drivers. The fatal crash risk of a driver distracted by a cellphone is still 1.76 to 3.17 times greater than that of a focused driver.

4. Externalities and Public Policy

In this section, we consider the public policy implications of the estimates obtained in the prior section. In the spirit of L&P, we begin assessing the negative externalities of distracted driving by calculating the number of traffic fatalities that would have been avoided if a driver had not been distracted (i.e., avoidable deaths). Following L&P, we first assume that if a distracted driver dies in a crash that she causes, then she bears the cost of her actions and is not classified as an externality. In effect, this assumption implies that the distracted driver considered all associated risk when making the choice to drive distracted. In addition, it does not internalize other noneconomic costs, such as the suffering of friends and family. Similarly, we also assume that passengers who died in a distracted driver's vehicle were willing participants who also assumed the risk associated with riding with a distracted driver, meaning that they are also not considered as an externality.[13] Finally, because this analysis is limited strictly to deaths in fatal crashes, it does not include other costs associated with non-fatal injuries, property damage, and other behavioral changes (e.g., focused drivers' fear of being struck by a distracted driver).

Table 12 displays the estimates of the negative externalities of distracted driving for each year of our sample.[14] For context, we explicitly describe the calculation of the year 2000 estimates, but the same

[13] In Table 12, we also present alternate estimates that relax this assumption.
[14] Note that, for ease of reference, Column 1 of the table includes the year-specific values of θ derived from our earlier estimation procedure which we use to explicitly estimate externalities.

logic applies to the estimates of all years. First, in 2000, there were 51 drivers killed in two vehicle crashes when both drivers were distracted. We assume that fault is evenly divided between the vehicle that caused the crash and the other vehicle and therefore categorize half of these deaths (25.5) as externalities.[15] Based on our model, $(\theta - 1)/\theta$ or 73.57 percent of these deaths would have been avoided had the driver at fault not been distracted, which translates to approximately 19 avoidable deaths from this category of drivers. An additional 568 fatalities resulted among occupants of vehicles driven by focused drivers that were involved in a two-car crash where the other vehicle was driven by a distracted driver. Based on our model, $(\theta - 1)/(\theta + 1)$ or 58.19 percent of these deaths would have been avoided had the driver of the other vehicle not been distracted, which translates to approximately 330 additional avoidable deaths. Considering the one fatality among occupants of vehicles driven by focused drivers involved in three car crashes with two distracted drivers and one focused driver, we estimate $((\theta\ x\ 2) - 2)/((\theta\ x\ 2) + 2)$, or 64.98 percent of that death to be avoidable. Similarly, considering the 110 fatalities among occupants of vehicles driven by focused drivers involved in three car crashes with one distracted driver and two focused drivers, we estimate $(\theta - 1)/(\theta + 2)$, or 48.12 percent of those deaths to be avoidable.

[15] In years when multi-vehicle crashes occurred involving three or more vehicles, all with distracted drivers, the same assumption is made. For example, in three car crashes in which all three drivers were distracted, we take the sum of all fatalities and scale by 2/3.

Table 12: Estimates of Fatality Externalities and Insurance Costs

Year	Theta	Avoidable Deaths (excluding passengers)	Avoidable Deaths (including passengers)	Avoidable Insurance Losses (000s)	Insurance Surcharge
2000	3.78	403	924	$2,434,344	$468
2001	3.49	382	863	2,728,655	486
2002	1.86	276	561	2,757,986	271
2003	1.43	228	441	2,481,445	168
2004	2.31	329	714	3,022,028	341
2005	2.00	273	553	2,703,272	299
2006	2.69	444	885	3,709,517	381
2007	3.55	489	1,026	3,942,820	483
2008	3.82	513	1,094	4,462,019	507
2009	3.51	442	987	4,851,473	485
2010	2.51	249	488	2,864,871	390
2011	2.39	237	463	3,137,491	392
2012	2.81	146	295	1,554,589	454
2013	2.62	119	223	1,440,689	442
2014	2.95	146	249	1,524,864	506
2015	2.74	155	269	1,755,473	512
2016	2.75	299	522	3,811,704	565
2017	2.23	221	385	3,584,267	478
2018	2.01	186	296	3,119,137	424
Average	n/a	291	591	$2,941,402	$424
Total	n/a	5,537	11,238	$55,886,644	$8,052

Note:

Summing the avoidable deaths suggests that 403 deaths would have been avoided in 2000 if drivers had not been distracted. This figure is reported in column 2 of Table 12, as well as the avoidable deaths for each of the subsequent years in our sample period. In total, we estimate that approximately 5,537 deaths could have been avoided during the years 2000 through 2018 if drivers had not been distracted. Note also that the figures reported in Column 2 are a conservative estimate, in that they do not classify fatalities to passengers in distracted drivers' vehicles as externalities. If we make the more realistic assumption that passengers do not assume the risk of the driver of their vehicle being distracted, and therefore include these passengers as externalities, the number of avoidable deaths during the years 2000 through 2018 increases to approximately 11,237 (Column 3, Table 12).[16]

Many studies attempt to determine the value of a statistical life (e.g. Viscusi, 1992, Viscusi and Masterman, 2017) and, based on the work presented in these studies, the U.S. Department of Transportation currently estimates the value of a statistical life at $11.6.[17] Multiplying this value by the estimated 5,537 avoidable distracted driving deaths that we conservatively estimate occurred during our sample period suggests the externality associated with lives lost due to distracted driving totaled approximately $64 billion between 2000 and 2018. If we categorize passengers in vehicles driven by distracted drivers as an externality, then the total externality associated with distracted driving rises to approximately $130 billion between 2000 and 2018. Further, both figures ($64 billion and $130 billion) represent externality cost estimates of fatalities only, not including the costs of non-fatal injuries, property losses, and other noneconomic losses in our analysis.

Following L&P, we contextualize the cost of the externality by evaluating the cost of distracted driving per mile. To do so, we first rely on our prior analysis to extract the implied fraction of distracted drivers in any given year (see Table 12). Then, for each year, we multiply the fraction of distracted drivers by the total vehicle miles traveled (available from the Federal Highway Administration) to obtain the implied miles driven by distracted drivers, which allows us to allocate the externality cost in a given year across miles driven by distracted drivers. For example, in 2000, the FHA estimates approximately 2.7 trillion vehicle miles were driven. In 2000, we estimate that approximately 2.75 percent of drivers were distracted and that the total cost of externalities, conservatively estimated was approximately $4.7 billion, which implies a negative externality of approximately 6 cents per mile driven by distracted

[16] Note that passengers of distracted drivers are in some ways less able to consent to the dangerous behavior than are passengers of intoxicated drivers, because intoxicated drivers are generally intoxicated at the beginning of a trip, but distracted drivers can be distracted intermittently. On the other hand, passengers are a common source of distraction for drivers.

[17] Information reported current as of 2020. See https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis.

drivers. Using the same process for all years in our sample period suggests an average negative externality of approximately 3 cents per mile driven by distracted drivers between 2000 and 2018. If we repeat the analysis but include passengers in vehicles driven by distracted drivers, the estimated negative externality increases to approximately 7 cents per mile driven by distracted drivers during the years 2000 through 2018.

We estimate the implied personal automobile insurance policy surcharge necessary to recover the insurance losses attributable to distracted driving to estimate the non-fatal externalities of distracted driving. We use data from the National Association of Insurance Commissioners (NAIC) to calculate the losses paid by all U.S. personal automobile insurance companies for each year from 2000 through 2018. To estimate the avoidable insurance losses, we make the following assumptions:

1. The percentages of one-car, two-car, and three-car fatal crashes to all fatal crashes are the same as the percentages of one-car, two-car and three-car crashes to all crashes;
2. The relative riskiness of distracted drivers causing fatal crashes is the same as that of them causing all crashes;
3. On average, the loss per car is the same regardless how many distracted drivers are involved.

With the above assumptions, we can estimate the avoidable insurance losses in a similar way as we did for the avoidable fatalities. Notice that in estimating avoidable insurance losses, there are not "externalities," so we consider the entire portion of insured losses that is avoidable. As given in Column 4 of Table 12, avoidable automobile insurance losses attributable to distracted driving ranged between $1.4 billion and $4.8 billion during of our sample period. Overall, we estimate that approximately $55.9 billion in personal automobile insurance losses could have been avoided if drivers were not distracted.

One method of internalizing these costs to distracted drivers is to have an insurance surcharge for drivers cited for distracted driving. Using the estimates of avoidable insurance losses to estimate an implied insurance policy surcharge requires that we next need to identify the number of citations given to distracted drivers in each year of our sample. Citation data pertaining to distracted driving are difficult to obtain and we are therefore required to rely on Rudisill and Zhu (2016), who estimate that approximately

2,607 citations per 100,000 licensed drivers are issued for distracted driving violations.[18] Using this citation rate, alongside the number of licensed drivers (from FHA), our estimates of the proportion of distracted drivers, and our estimates of the avoidable insurance losses, we can calculate an implied insurance surcharge by distributing avoidable insurance losses over the expected number of distracted driving citations in a given year.

The implied personal automobile insurance surcharges for each year of our sample are given in Column 5 of Table 12. The implied surcharge ranges from approximately $168 per driver in 2004 to $565 per driver in 20016. The average implied surcharge for the sample period is approximately $424. For context, this figure implies that drivers cited for distracted driving between 2000 and 2018 should have been charged an additional $424 by their personal automobile insurance company to allow the insurers to recover the cost of distracted driving on automobile insurance losses.

5. Conclusions

We develop and apply a methodology that measures the risks posed by distracted driving. The method builds on L&P's model of drinking and driving, which relies on fatal crash data from FARS. FARS data are appropriate for this application because every fatal automobile crash is investigated and recorded and a consistent framework that is not used for other crashes. This methodology allows for extracting from the FARS data estimates of distracted driving frequency and the relative riskiness of distracted driving. By relying on a standardized data source, this methodology solves some of the concerns on how data on distracted driving are collected.

[18] The citation data from Rudisill and Zhu (2016) pertain only to the years 2010 and 2013. We acknowledge the shortcomings associated with applying the average citation rate reported by Rudisill and Zhu (2016) to all states and all years in our study but we are unaware of any other source for estimating the distracted driving citation rate. To extend Rudisill and Zhu (2016) to our sample, we assume that the enforcement rate from 2010-2013 persists over the sample and all states in the US have a distracted driving moving violation. Note that, if the citation rate were half of what was reported by Rudisill and Zhu (2016), the implied average surcharge would be $848 and if the citation rate were double reported by Rudisill and Zhu (2016), the implied average annual surcharge would be $212. As such, even if our assumption of the distracted driving citation rate is off by a significant magnitude (which we do not believe it to be), our analysis still suggests a non-trivial insurance surcharge is necessary to offset the cost of distracted driving to automobile insurance companies.

Estimates indicate that distracted drivers are approximately three times more likely to cause a fatal crash than focused drivers. They also represent three to four percent of drivers on the road at any given time. The distractions associated with cellphone use are not as great as distractions from other sources regarding their effect on the relative risk of causing a fatal crash. The fatal externalities imply a cost of \$.03 to \$.07 per mile. The insurance cost externalities could be internalized with annual insurance surcharges for distracted driving citations of \$424.

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